Stimulating Consumption at Low Budget: Evidence from a Large-scale Policy Experiment amid the COVID-19 Pandemic

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Abstract

We use a novel panel with detailed transaction records of more than one million de-identified individuals to study the effect of a large-scale Chinese government-issued digital coupon program on consumer spending. At the core of this stimulus program are a set of salient features that drive the marginal propensity to consume (MPC) to the range of 3.4 to 5.8, an order of magnitude larger than those in previous studies. Testing between different models of consumer behaviors, we find that a behavioral model with mental accounting and loss framing can match the empirical evidence from the field. Our analysis, by illustrating the importance of embedding behavioral factors into the design and implementation of public policy, inform the current debate about cost effective policy tools to recover the economy.

JEL Codes: D12, H31, E21, E61, E62, H53

Keywords: fiscal stimulus program, marginal propensity to consume (MPC), field experiment, Chinese digital coupon, behavioral economics, COVID-19

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1 Introduction

In response to economic recessions, governments often resort to stimulus payments to spur consumer spending and stimulate the economy through a multiplier effect.[1] The effectiveness of stimulus payments depends on consumers' marginal propensity to consume (MPC hereafter). Past research on households' responses to various stimulus programs such as tax rebate, cash payment and shopping coupon found the MPCs in the range between 0.1 and 0.8.[2] Would a carefully designed stimulus program be able to achieve a larger effect with higher MPC? If so, what are the unique features and underlying mechanisms that contribute to such effect? What account for the heterogeneity of MPCs across a broad set of variables?

In this paper, we examine a large-scale government-issued digital coupon program in China in response to the COVID-19 pandemic, using the high-frequency transaction-level data of more than 1 million de-identified consumers. Exploiting a difference-in-differences approach, we estimate the causal effects of the program on consumption and explore the mechanisms driving such effects. Empirical evidence from the field shows that consumers are highly responsive to the digital coupons issued by the government. Our point estimates report MPCs ranging from 3.4 to 5.8, an order of magnitude larger than those in previous studies. We also find that there is substantial heterogeneity in MPCs across consumers and variation in coupon design, which suggests that targeted distribution and change of design can potentially increase the effectiveness of stimulus payments. Testing between different models of consumer behavior, we provide evidence that our empirical results are largely consistent with a behavioral model, with mental accounting and loss framing being the behavioral factors of first-order importance. Our paper illustrates the importance of considering behavioral factors in the design and implementation of public policy.

The digital coupons program is a new policy tool utilized by the Chinese local governments to stimulate consumption. Since mid-March of 2020, more than 170 cities in 28 provinces have rolled out their digital coupon programs (as of May 9, 2020), and the amounts of government subsidies

[1] For example, in 1999, the Japanese government distributed shopping coupons worth about 200 dollars to eligible families to stimulate spending; in early 2009, Taiwan distributed vouchers worth about 120 dollars to every citizen; to combat the economic damage caused by the COVID-19, the US government passed the 2020 CARES Act on March 27, which authorizes direct cash payments to households.

[2] For example, Johnson et al. (2006) study the 2001 tax rebates in the US and find that households spent 20-40 percent on non-durable goods during the quarter in which they received the rebates; examining the veteran's bonus of 1936, which paid about 2 percent of GDP to 3.2 million veterans, Hausman (2016) finds that the MPCs are between 0.6 and 0.75; Kan et al. (2017)use survey data to investigate consumers' responses to the 2009 Taiwan shopping voucher program and find an MPC of 0.24. Hsieh et al. (2010) find that Japan's shopping coupons in 1999 induced a modest marginal propensity to consume on semi-durables in the magnitude of 0.1-0.2.

range from millions to billions Chinese yuan in magnitude across cities. The program departs from other commonly adopted fiscal stimulus programs such as cash payment or tax rebate in several salient ways. First, the coupon typically takes the form of saving with certain amount of spending, e.g. "spend RMB 40, get RMB 10 off", and hence has the nature of "use-it-or-lose-it".

Second, unlike the previous government-initiated shopping coupon programs (e.g., Hsieh et al., 2010; Kan et al., 2017), which involve relatively large coupon amount in hundred dollars and redemption period of several months, this coupon program is carried out with small amount per voucher and typically a much shorter duration of one week or two. Take the coupon program rolled out in Hangzhou on March 27[3] as the example – the coupon packet is valued at RMB 50(US $7) with five separate "spend RMB 40, get RMB 10 off" vouchers, and only valid for seven days.

Third, the disbursement method of the coupons is unconventional. Taking advantage of the rapid deployment of mobile payment system, the coupons are distributed through major mobile payment platforms.[4] The coupon program varies across cities in terms of the rolling out date, coupon value, scale and the specific platform employed. While all residents in a city are eligible for the coupon, they have to actively acquire it from the pre-announced mobile platform on a "first-come-first-serve" base. The number of coupon packets in each round is limited. Therefore, not all residents get the coupons.

We employ a unique and comprehensive data from Hangzhou, the capital city of Zhejiang province with 10 million residents, to study the effectiveness of the digital coupon program. Hangzhou is one of the first cities that experimented large scale digital coupon disbursement. Its practice has been widely followed by other Chinese cities. Between March 27 and April 16, Hangzhou municipal government rolled out three waves of digital coupons on a weekly base, covering 1.5 million to 2 million individuals in each wave. The total government subsidy reaches RMB 400 million. The coupons are distributed through Alipay, one of the leading mobile payment platforms in China. Our data is from Alipay, which tracks detailed de-identified transaction data at individual level of millions of users in the city. The digital coupon, automatically linked to an individual's Alipay account, is non-transferrable.

The detailed transaction-level data allow us to track who have obtained the digital coupons, whether and in what settings the coupons have been redeemed. We hence are able to minimize

[3]All the dates refer to year 2020 if not explicitly noted.

[4]Alibaba and Tencent are the two leading mobile payment platforms in China, each with close to 1 billion user accounts. The two platforms together account for more than 90 percent of the market share in China. In 2018, the transaction value of mobile payments in China totaled $41.5 trillion, three times of the total transaction value in the US.

measurement error in estimating consumers' short term responses to the policy. Exploiting the experimental data at individual level from the field, we apply a difference-in-differences (DID) approach to evaluate the effect of coupon acquisition on spending. Our focal study is the first wave of coupon disbursed on March 27 to 2 million residents in Hangzhou, accounting for 20 percent of the population. Each coupon packet includes five separate "spend RMB 40, get RMB 10 off" vouchers which are valid for redemption in offline purchases from March 27 to April 2. Specifically, we take a random sample of 100,000 consumers who successfully obtained the coupon packet as the treatment group, and construct a control group of the same size from those who attempted but failed to obtain the coupon due to limited offering. The digital technology enables us to track individual activities on the mobile payment platform and identify a group of consumers similar to the treatment group to alleviate the self-selection concern.

By comparing the spending of the individuals in the treatment and control group during a seven-day period before March 27 and the seven days thereafter when the coupons were valid for redemption, we find a treatment effect of RMB 125. That is, the individuals who obtained the coupon on average spent RMB 125 more during the coupon week than their counterparts in the control group. Considering the fact that on average each person redeemed 3.5 coupons during the week, the effective government subsidy is RMB 35 per person, suggesting that the MPC is 3.5 – that is, each RMB 1 of government subsidy induces RMB 3.5 of excess spending. Analysis of the spending by category reveals that the excess spending mainly concentrates on daily purchases such as catering service and food and drinks.

The second wave of government coupon, rolled out on April 3 and valid for seven days, has a different design. The coupon packet includes three vouchers with larger minimum spending requirement as well as larger amounts of government subsidy (e.g. "spend RMB 200, get RMB 35 off"; "spend RMB 300, get RMB 45 off") than the first wave. It allows us to examine how variation in coupon design affects consumer behavior. Empirical analysis show that coupons with higher minimum spending are able to spur larger purchases. The overall MPC in this wave is 5.8.

We further study the dynamic effect of coupon issuance. There are two important questions here. One is whether the short duration of the coupon induces intertemporal substitution, i.e., the increased spending during the coupon week crowds out consumption in the subsequent period. If this is the case, the policy is ineffective to stimulate spending when taking both periods into consideration. To examine the intertemporal effect, we track a random sample of individuals who successfully obtained coupon packets in the first wave but not the second wave, and extend the observation period to the week after the coupon expiration date. Our DID analysis indicates that the expenditure level of the treatment group during the post coupon week is not statistically different from the control group. In other words, there is no evidence of crowd out effect immediately following coupon usage.

Another question is whether the coupon effect wears out easily when the digital coupon is repeatedly used. While the first wave and second wave are not directly comparable due to differences in design, the fact that the third wave coupon (rolling out on April 10) has exactly the same design as the first wave allows us to address this question. We find the estimated treatment effect of the third wave not statistically different from the first wave, with the estimated MPC of 3.4. This result suggests that the repeated coupon disbursement does not compromise the effect in boosting consumption, at least during the window of this study.

We also explore heterogeneity in the treatment effect by exploiting the fact that we observe characteristics of the account holders as well as their past transactions. We find that the coupon effect is more pronounced among the groups with lower baseline expenditure, less online shopping experience and older age.

Although our empirical results do not depend on any particular economic models, they are in sharp contrast to the standard permanent income or lifecycle theory of consumption (Modigliani and Brumberg, 1954; Friedman, 1957). We do not find supporting evidence for the liquidity constraint hypothesis either. Our results are largely consistent with a reference-dependent model with both mental accounting and loss framing. In line with mental accounting (Shefrin and Thaler, 1981; Thaler, 1999), consumers seem to treat the digital coupon as a separate account from their regular weekly budget and exhibit a higher propensity to consume when receiving the small windfall (i.e., the digital coupon packet). The effect is further amplified by loss framing, which results from the design and implementation of the digital coupon program. One of the salient features of the digital coupon is its nature of "use-it-or-lose-it". The government subsidy is not cash equivalent and it cannot be captured unless one's spending reaches a certain amount. The loss framing incentivizes consumers to redeem the coupons, which incurs additional spending. The heterogeneity in coupon responsiveness across consumer groups, while inconsistent with the predictions of standard economic models, is in line with the behavioral explanations.

This paper provides the first study of the large scale digital coupon program in China and our research sheds light on policy design in stimulating consumption. To combat the economic downturn caused by COVID-19, improving the effectiveness of a fiscal stimulus payment program is critical. Our results show that the "small size, short duration" digital coupon program works well in an economy where the households' precautionary savings traditionally are at a high level, and the local governments' fiscal budgets are stretched. In addition, the majority of the coupons are redeemed at small businesses, which are most vulnerable to the pandemic shock and in great need of recovery.[5] As the digital coupons are disbursed through mobile payment platforms, their use can be easily tracked, and the results can be accurately and timely assessed, which allows the policy makers to target the most responsive consumer groups, adjust coupon design, scale up or down its disbursement, and decide disbursement frequency. In the cost-benefit framework, the effectiveness of the digital coupon program is striking. Our back-of-the-envelope calculation shows that the program, if scaled nation-wide among China's about 400 prefecture-level municipal cities and over 1 billion mobile payment account holders, can lead to a 4.25 percent increase in retail sales, which translates to a GDP growth of 2.46 percentage points.[6]

Our evaluation of the highly localized Chinese coupon program is subject to several caveats. First, while the program may have large and positive effects on the entire local economy rather than the treated only, with the data at hand, we are unable to estimate the indirect effects – our estimates of the economic magnitude of the policy may be downwardly biased. Second, at the aggregate level, it does not consider the general equilibrium effects that could have amplified or diminished the initial spending impulses. In addition, although we use observational data in this paper, our research setting is similar to a randomized control trial. The external validity challenge on randomized control trials applies to our paper – the results based on the policy experiment in Hangzhou do not necessarily extend beyond (Banerjee et al., 2017; Duflo, 2017).

Despite these caveats, our paper is relevant for policy making in the current economic recession, when governments are in an urgent need to bring forward cost effective policy tools to recover the economy. Our analysis suggests that when breaking the usual one-time, blanket and nation-wide stimulus program into multi-round localized policy interventions, the program could be more effectively configured, in both design and implementation, to achieve the intended goals.

Our study builds on a much broader literature that investigates consumers' responses to fiscal stimulus payments (e.g., Johnson et al., 2006; Agarwal et al., 2007; Parker et al., 2013; Agarwal

[5]According to the National Statistics Bureau of China, there are more than 110 million small and individual businesses operating in China now, which absorb more than 80 percent of urban employment.

[6]Here we assume that the "small size, short duration" digital coupon can be repeatedly used by the Chinese local governments in the next six months or so, and each mobile payment account holder on average obtains RMB 500. While the total amount of government spending is RMB500 billion, accounting for 0.5 percent of GDP, it generates excess spending of RMB 1.75trillion.

and Qian, 2014). A small number of papers use high-frequency transaction-level data to study customers' responses to tax rebates or stimulus payments (e.g., Broda et al., 2014; Baker et al., 2020). Our paper adds to this line of research by using a large scale high-frequency transaction-level data to estimate the effectiveness of the Chinese version of fiscal stimulus payment program, the digital coupon issued by local governments, and document the MPCs an order of magnitude larger than the previous studies.

This paper also relates to a more recent literature showing that incorporating behavioral considerations into public policy making leads to more desirable policy outcome.[7] Thaler and Sunstein (2008) show that public policy including subtle behavioral interventions is more robust. Fryer et al. (2018) document the evidence of loss framing effect in incentivizing school teachers to improve student performance. Madrian and Shea (2001) and Chetty et al. (2014) show that properly setting default (no action) options can significantly increase saving in retirement accounts. Beatty et al. (2014) study the UK Winter Fuel Payment and find that the labelling effect of cash transfer induces higher spending in the category. Sharing similar spirit, our paper shows that fiscal stimulus program embedded with features in accordance with behavioral factors such as mental accounting and loss aversion generates much higher MPCs, and costs much less.

Finally, this paper also contributes to the on-going discussions of the economic impact of the COVID-19 pandemic and the effects of fiscal stimulus payments.[8] Baker et al. (2020) is most relevant to ours. They use high-frequency transaction level data to examine households' spending responses to the 2020 CARES Act in the US, and document the MPCs of 0.25-0.35 during the first 10 days of receiving the stimulus payments. They suggest that liquidity constraints explain heterogeneity in MPCs.

The rest of the paper is organized as follows. Section 2 describes institutional background and the digital coupon program implemented in the Chinese cities. Section 3 discusses the data and empirical strategy. Section 4 estimates the MPCs of the digital coupon program and documents the main findings from multiple coupon waves. Section 5 examines heterogeneity in coupon responsiveness across consumer groups and conducts several robustness checks. Section 6 analyzes the mechanisms that drive our major findings. Section 7 discusses policy implications followed by conclusion in Section 8.

[7]See Dellavigna (2009) for a more general survey on the psychology and economics literatures; and Chetty (2015) for a survey on the literature of applying behavioral models to public policy making.

[8]For example, Chen et al. (2020) use transaction-level data to study the impact of the COVID-19 outbreak on consumption in China; Baker et al. (2020) study the impact of pandemic on household spending in US; Coibion et al. (2020) and Fairlie et al. (2020) examine the short-term employment effects of the pandemic.

2 Research Background

2.1 The COVID-19 Pandemic and Stimulus Payments in China

China was the first country that experienced large-scale outbreak of the virus since January 2020. The epidemic brought much of the economy to a standstill with wide lockdowns, and caused a dramatic increase in unemployment and contraction of real economic activities. According to the National Bureau of Statistics of China, China's GDP contracted by 6.8 percent in the first quarter of 2020 – the worst growth record in more than four decades – and retail sales of consumer goods and services fell by 19 percent compared with a year earlier. Labor statistics show that by February, the unemployment rate in China rose to 6.2 percent, representing a one percentage point increase within three months.

For policy makers, stimulating consumption is one of the top priorities to revive the economy. First, finding effective ways to spur consumption would save many small businesses from going bankrupt and temper the increase in unemployment rate. Second, consumption is now the main engine of China's growth, contributing to 57.8 percent of GDP growth in 2019. Unlike economies such as the US, UK, Japan and Singapore, where employing cash payment or tax rebate to stimulate economy has a long history, China had never implemented large-scale nationwide fiscal stimulus payment programs. In an economy where people value frugality, the household savings rate has been very high.[9] Cash payments and alike, if any, may be immediately put into bank saving accounts, and generate inconsequential impact on consumption. In addition, during hard times, the governments at all levels are constrained by available financial resources, which means large disbursement of cash payments is unlikely a policy option.

Yet the economic damage caused by COVID-19 is severe and continuing, and the retail sector was hit the most. Chen et al. (2020) report that the pandemic caused more than 30 percent of decline in spending on goods and services in China. Even after the spread of virus had been contained and economic activities had been resumed beginning in early March, the recovery of retail sector was much slower than expected. To kick-start much needed retail spending, local governments started to experiment with issuing "consumption coupon" since mid-March. As of

[9] According to the People's Bank of China (PBoC), by the end of Q1 of 2020, household savings had increased to RMB 87.8 trillion (about 88 percent of China's GDP), which represents an RMB 6.4 trillion increase from the previous year, out of concerns about the uncertainties caused by COVID-19 and its damage to the economy (data source: the PBoC website). See Wei and Zhang (2011) for what account for the high and rising household savings rate in China.

May 9, more than 170 cities issued more than RMB 19 billion worth of consumption coupons.[10] Figure 1 shows the time series of the number of times "consumption coupon" appearing in key words search by Baidu search, an index that reflects the attention from the society. It reached the highest spike on March 27, when Hangzhou announced the largest consumption coupon program among all Chinese cities.

2.2 Hangzhou Digital Coupon Program

Hangzhou is the capital city of Zhejiang province, one of the most economically developed regions in China. Hangzhou has 10 million residents and boasts a GDP per capita of RMB 152,465 (approximately US$22,000), 2.15 times of the national average in 2019. Zhejiang was the first in the country to raise the risk management response to Level 1, the highest public health emergency level, in response to the outbreak of COVID-19 in January. Multiple prevention measures were implemented including mobility restrictions and closing down shops and businesses. Zhejiang lowered the local response level to Level 2 on March 2 when the number of confirmed cases stabilized for an extended period and further to Level 3 on March 23. Economic activities started to resume in March.

On March 26, Hangzhou municipal government announced its plan to issue RMB 500 million in digital coupons, rolling out in waves from March 27 to May 31, 2020, with the objective to rekindle consumer demand and support local commerce which was severely affected by the COVID-19 outbreak. All residents in Hangzhou (including visitors from outside Hangzhou) are eligible for the coupons distributed through the mobile payment platform Alipay. Each person is limited to one claim per wave. The details of coupon design are released one day before each issuance wave. Our study focuses on the first three waves.[11]

The first wave of 2 million coupon packets, covering one fifth of the population, was released on March 27 at 8 am. Each coupon packet includes five separate vouchers of "spend RMB 40, get RMB 10 off" ("RMB 40 -10" thereafter) valid for seven days from March 27 to April 2.[12] The government subsidy is RMB 50 per coupon packet. The coupons can be used in nearly all the physical merchants in Hangzhou when a purchase meets the minimum requirement of RMB 40.

[10] https://news.cgtn.com/news/2020-05-09/China-distributes-19-billion-yuan-in-coupons-to-stimulate-consumption-QlxEgDNbI4/index.html.

[11] See Table A1 in the Appendix for the summary of the multiple coupon waves in Hangzhou.

[12] On April 1, another 2 million packets of wave I coupon were released. Those who had received the coupon were not eligible to apply again. In our analysis below, we only focus on the initial rollout of the wave I coupon. We are careful in constructing the treatment and control groups to avoid the potential confounding effects induced by the April 1 batch.

The second batch of coupons was released on April 3 at 10am with a total quantity of 1.5 million packets. Each coupon packet includes three different vouchers, one "RMB 100 -20" voucher, one "RMB 200 -35" voucher and one "RMB 300 -45" voucher. They are valid from April 3 to April 9. The government subsidy is RMB 100 per coupon packet. The coupons are redeemable at participating merchants. The third wave coupon was rolled out on April 10 at 10am and the total quantity was again 1.5 million. The coupon design and rules are the same as the first wave, with government subsidy of RMB 50 per packet. In response to this consumption stimulus, many local merchants also offered various discounts and promotions to attract consumers. The coupons are applied to the final transaction amount after merchant discounts.

2.3 Coupon Acquisition and Redemption

The government coupons are distributed through mobile platforms, taking advantage of the fact that China has a high penetration rate of smartphones and mobile payment. A recent survey by PwC shows the mobile payment penetration rate in China is 86 percent in 2019, the highest in the world.[13] Mobile payment is not only the dominant choice for online transactions but also has become ubiquitous for offline purchases through QR code scanning, quickly replacing cash payment in recent years. From the government perspective, the advantage of digital coupon is that it can be released in a short time with little cost. In addition, one can easily track coupon redemption.

Hangzhou's digital coupon program was rolled out on Alipay, the dominant mobile payment platform adopted in Hangzhou.[14] When coupons were released, residents at Hangzhou can acquire the coupons by logging onto the Alipay mobile app. The coupon application page is displayed as the front page for Hangzhou users or one can search "Hangzhou Consumption Coupon" to locate the page. Figure 2A shows a screen shot of the page when the first wave coupon rolled out. Simply tap the application button and a coupon packet would appear in the account and redeemable immediately. The first release of digital coupons on March 27 took 38 minutes before all the 2 million coupon packets were claimed. The second wave on April 3 with 1.5 million coupon packets was claimed in less than 3 minutes and the third wave issued on April 10 was claimed in less than 2 minutes.

The vouchers can only be redeemed physically in stores at Hangzhou and not applicable to

[13]https://www.pwc.com/gx/en/consumer-markets/consumer-insights-survey/2019/report.pdf.

[14]Founded by Alibaba group in 2004, Alipay is the leading mobile payment platform in China with a market share over 50 percent. Its market share is particularly high in Hangzhou, where Alibaba is headquartered. Our survey of 247 respondents shows 91.5% of the respondents use Alipay as their primary payment method.

online transactions as a way to encourage people to go out after a long period of quarantine. The redemption process is easy. When an offline purchase meets the minimum usage requirement of a voucher, the voucher will be automatically applied to the transaction if a consumer uses Alipay and has a valid voucher in the account. For example, a consumer made a purchase in a grocery store on March 30 with a total amount of RMB 77.9 (as Figure 2B shows). She had three valid vouchers of "RMB 40 -10" in her account and this transaction automatically redeemed one of the vouchers and saved her RMB 10 from her own payment. This RMB 10 is paid by government to the merchant. At most one voucher can be applied in each transaction. In wave I and III, coupons are redeemable at nearly all the offline stores in Hangzhou and the merchants do not need to register to participate in the program. Wave II coupons are acceptable at participating merchants in the city.

3 Empirical Strategy and Data

3.1 Empirical Methodology

The main objective of the paper is to evaluate the effect of the government coupon program in the short run. Although the coupons are framed in the consumption context, they are not necessarily effective in increasing spending if consumers apply the coupons toward planned spending and turned the government subsidy into saving. We exploit the fact that only a fraction of Hangzhou residents acquired the government coupons in each wave and employ a difference-in-differences approach to evaluate the overall effect of digital coupon on individuals' expenditure.

The identification challenge is that coupons are not randomly assigned and those who applied for the coupon could exhibit different expenditure pattern from those who did not. To alleviate the self-selection concern, we construct the control group as those who attempted but failed to acquire the coupon due to limited offerings. We identify this group of consumers by tracking through their activities on the mobile payment platform on the coupon issuance day. These individuals could potentially be the coupon users and presumably are more similar to the treatment group who obtained the coupon packets.

Our focal study is the first wave coupon issued on March 27 with a 7-day redemption period from March 27 to April 2. The treatment group in our empirical analysis involves a random sample of individuals who successfully acquired the coupon. The control group is a random sample of individually who attempted on March 27 but failed and have no coupon throughout the seven days. Our examination window is a 14-day period, which includes a one-week pre-treatment period, March 20 to March 26 (03/20 - 03/26) and a one-week post-treatment or coupon redemption period, March 27 to April 2 (03/27-04/02). We use the following specification to estimate the effect of coupon acquisition on expenditure:

$$y_{it} = \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_t + \alpha_3 Treat_i \times Post_t + \gamma X_{it} + \varepsilon_{it} \tag{1}$$

The dependent variable y_{it} denotes spending by individual i in period t ($t = 1$, pre-treatment period; $t = 2$, post-treatment period). In some specifications, y_{it} is further decomposed into online and offline spending or spending on different categories. The variable $Treat_{it}$ is an indicator which is equal to one if individual i is in the treatment group and zero otherwise, and the coefficient α_1 captures any baseline difference in spending between the treatment and control group. $Post_t$ is a dummy variable indicating whether t refers to the post-treatment or coupon redemption period. The coefficient α_2 captures any time trend in spending across periods. The vector X_{it} controls for other observed individual characteristics that may explain the variation in spending. Standard errors are clustered at the individual level.

The coefficient of primary interest is α_3, which estimates the average excess spending by the treated consumers during the coupon week relative to consumers from the control group. When estimating Equation (1), we do not differentiate the number of coupons redeemed during the week and only consider the average treatment effect of using the digital coupon. The DID framework is able to identify the excess spending (if any) induced by coupon by parceling out the planned or budgeted weekly spending inferred from the control group.

We estimate MPC using the specification: $MPC = \frac{\alpha_3}{amount\,redeemed}$, where α_3 is the coupon-induced excess spending, estimated from Equation (1), and *amount redeemed* equals the average amount of government subsidy per person based on the actual redemption. For example, if the coupon receivers in the first wave redeemed three vouchers per person on average, then the average amount of redemption is RMB 30 as the government subsidy is RMB 10 per voucher.

We also use the logarithm of y_{it} as the dependent variable to estimate Equation (1). In this case, $\alpha_3 \times 100\%$ measures the increase of the treated consumers' spending relative to the control group in the treatment period (in percentage). When we divide α_3 by the government subsidy rate, e.g. 25% for Wave I coupon, we obtain the implied elasticity (e), which measures the sensitivity of the coupon-induced spending to change in government subsidy rate. Throughout our analysis, we mainly rely on MPC to interpret the magnitude of the coupon effect. In some specifications, we use implied elasticity (e) to measure the effectiveness of the disbursement of digital coupons.

To evaluate how the coupon effect varies with different coupon design, we also estimate the treatment effect of the second wave of coupon, carried out from April 3 to April 9 (04/03-04/09), using the specification in Equation (1). Since all residents in Hangzhou are eligible for the new wave of coupon issuance, regardless of their outcome in the previous wave, the group of individuals with coupon may include those who obtained coupon in the first wave. We consider different ways to construct the treatment and control groups and will be explicit about the definition in the analysis below.

We further explore the intertemporal effect of coupon issuance using data from the first wave. Specifically, we track a random sample of individuals who received coupon packets in the first wave but not the second wave, and extend the observation period to a week after the expiration date of the first wave coupon (04/03-04/09). The corresponding control group in this analysis is a random sample of consumers who attempted to acquire coupons on March 27 but did not have coupon through April 9. We estimate the following model:

$$y_{it} = \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_t + \alpha_3 Post2_t + \alpha_4 Treat_i \times Post_t + \alpha_5 Treat_i \times Post2_t + \gamma X_{it} + \varepsilon_{it} \quad (2)$$

The difference between Models (1) and (2) is that we add a post-redemption period (04/03-04/09) to the analysis, indicated by the dummy variable $Post2_t$. Therefore, the total number of periods in this analysis is three, including the pre-coupon period (03/20 -03/26), the coupon week (03/27-04/02), and the post-redemption week (04/03-04/09). The coefficient α_4 estimates the treatment effect of coupon acquisition on spending during the coupon redemption week. Our primary focus is α_5, which estimates the lagged effect of coupon in the subsequent period. If the parameter is negative, it suggests that the treatment group would reduce their spending in the subsequent week after the expiration of the coupon, relative to the control group. The net effect of coupon issuance across the two periods is then $(\alpha_4 + \alpha_5)$.

3.2 Data

We use de-identified transaction-level data from Alipay for the analysis. The basic function of Alipay is an e-wallet, which allows users to transfer money and make payments for both online transactions and offline transactions through QR code scanning. Users can link their major bank accounts to the service. In addition, Alipay offers other financial services including virtual credit card services, *Huabei*, and financial management tools in the app. We have access to the de-identified account level transaction details for a total number of 1 million individuals sampled in this study.[15]

For each individual in the sample, we observe the complete transaction information of the account and information on the account holder's personal attributes such as gender and age. The transaction-level data include the transaction time, transaction amount, the usage of coupon (if any), merchant category and whether the transaction is online or offline. The advantage of this dataset is that we have complete record of coupon acquisition and redemption with little measurement error, while previous studies of government shopping coupon programs rely on survey and secondary data to infer the effectiveness of coupon issuance (Hsieh, Shimizutani and Hori, 2010; Kan, Peng and Wang 2017). The richness of the individual level information also allows us to better understand the heterogeneous responses to the coupon program.

For the purpose of our study, we first aggregate the transactions at individual-daily level and the main observation window is a 14-day period around coupon issuance. For example, the observation period of the first wave coupon is from March 20 to April 2. To control for spending behavior before the coupon program, we extend the observation period to six months before March 2020, which is from September 2019.

For the analysis of each coupon wave, we take a random sample of 100,000 users from the coupon receivers to construct the experiment group and 100,000 users who attempted but failed to obtain the coupon as the control group. In some cases, we construct multiple sets of experiment group and control group for a given coupon wave with varying restrictions. For example, we consider two methods in defining the treatment and control groups for Wave II coupons. In the first method, we define the treatment group as those who successfully obtained coupon on April 3 and the corresponding control group as those who attempted but failed to acquire coupon on the same day, without further restrictions. In the second method, we add a condition to exclude those who have been treated in the first wave in constructing the sample. The latter is to preclude the potential contamination of the lagged effect from the first wave coupon.

In Table 1 we report the summary statistics of the account holder's attributes and spending behavior of the treatment and control groups of Wave I and Wave II coupons. To minimize the influence of the outliers, we winsorize the variables of spending amount at the 99.5 percentile.

[15] The unique number of individuals is smaller than 1 million, as the same individuals could be in the control group for one wave coupon while in the treatment group for another wave.

Panel A reports the statistics of the Wave I sample. Panel B and C report the statistics of the two samples of experiment/control design from Wave II as described above. We notice that the experiment group and the control group are not directly comparable. For example, the control group exhibits considerably lower offline spending on average than the experiment group, although the discrepancy varies across samples. We conjecture that the difference in expenditure between the treatment and control group is related to payment habit. Some individuals may tend to use other payment methods for daily transactions and Alipay only captures a fraction of the total transactions. These consumers may fail to acquire coupons as they are less proficient in using Alipay app. This effect could be more pronounced for the initial launch of the coupon program on March 27.

To address the issue, we use the propensity score matching method (PSM hereafter) to construct a more comparable sample of those who successfully obtained the coupon and those who failed. The variables used for matching include age, gender, the average monthly spending in the last six months, the average spending in early March (03/01-03/19), and whether one has a *Huabei* account.[16] For each individual we compute the propensity score based on a logistic regression with the above variables and perform the nearest-neighbor matching. We drop the observations which cannot be matched, i.e., the gap of propensity scores exceeds the pre-specified threshold. The process results in 68,874 pairs of the matched treatment and control individuals for Wave I, and 76,466 or 77,422 matched pairs for Wave II. After matching, the differences between the treatment and control group are considerably reduced and almost indistinguishable.

3.3 Descriptive Analysis of the Coupon Program

We report the redemption information of the three coupon waves in this subsection. The redemption rate for the first wave coupon is 70 percent in our sample. That is, each coupon claimer on average redeemed 3.5 coupons during the seven days when the coupons were valid. Recall that the coupon packet includes five identical "spend RMB 40, get RMB 10 off" vouchers. The upper panel of Table 2 reports the distribution of coupon usage. About 88.3 percent individuals who successfully acquired the coupon packet used at least one voucher during the redemption period and 49.9 percent used all of the five vouchers. Taken together, the government subsidized approximately RMB 35 per coupon claimer. Across the seven days from March 27 to April 2, the redemption rate was relatively higher in the first and last two days of the redemption period than the three days in the

[16] We are not allowed to report summary statistics of some of these variables due to data sensitivity.

middle.

The second wave coupon packets include three different vouchers. The average redemption rate of the "RMB 100 -20" voucher is 68.5 percent; the redemption rates of the "RMB 200 -35" and "RMB 300 -45" vouchers are 61.4 percent and 63.5 percent respectively, as summarized in the lower panel of Table 2. On average, the government subsidized RMB 63.8 per coupon claimer. 32.3 percent of the subsidy was claimed in the first two days of the redemption week.

The design of the third wave coupon is the same as the first wave with five separate "RMB 40 -10" vouchers. The overall redemption rate in this wave is 82 percent, which amounts to a subsidy of RMB 41.2 per coupon receiver. More coupons were redeemed during the first three days, accounting for 55.6 percent of the total amount redeemed.

As model free evidence for the effectiveness of the coupon program, we show in Figure 3 the time-series plots of the average daily spending of the treatment group and the control group of the matched sample for the period before and after a coupon wave. Figure 3(a) and 3(b) display the data pattern for Wave I and Wave II respectively. The figure shows that the two groups followed a similar trend in total spending before the coupon rollout, and there is an immediate surge of spending by the treatment group following the receipt of coupons on the issuance day. The gap between the experiment and control groups persists during the whole coupon redemption period. It provides suggestive evidence that the government issued coupons effectively induced excess spending.

4 Main Results

4.1 The Effect of Coupon Acquisition on Total Spending

We first report the average effect of coupon acquisition on individual spending during the redemption window, which estimates the immediate effect of government coupon issuance. Table 3 presents the DID analysis of the first wave coupon by applying Equation (1). We performed the analysis on both the PSM matched sample and the unmatched sample. Columns (1) – (4) report the results from the full sample analysis while Columns (5)- (8) are from the PSM matched sample.

The coefficient in front of the interaction term $Treat \times Post$ measures the difference in spending of the treatment group in comparison with the control group during the seven-day coupon redemption window. Column (1) shows that individuals in the treatment group on average increased their total spending by RMB 124.6 in the coupon week relative to the controls, and the estimate using the matched sample in Column (5) is similar, RMB 133.7. The effect is both statistically and economically significant. Using the estimate from the original sample, we find that government subsidy of RMB 35 per coupon (considering the redemption rate) induced RMB 124.6 unplanned spending, corresponding to an MPC of 3.5.

Column (2) reports the result using the logarithm of an individual's weekly spending as the dependent variable. The coefficient estimate of the term $Treat \times Post$ is 0.762, which implies that the coupon increased the total spending of those in the treatment group by 72.6 percent, relative to those who did not get coupons in the redemption week. The implied elasticity is 3, given the 25 percent (RMB 10 out of RMB 40) government subsidy rate. These results suggest that the coupon receivers are highly responsive to the government subsidy in the form of the digital coupon.

Columns (3) and (4) decompose the total spending into offline spending and online spending. The results indicate that the offline payment increased by RMB 145.5 while the online spending was reduced by RMB 23.4 during the coupon week. This is not surprising as the coupon program is aimed at stimulating local business and the coupons are applicable to offline purchases only. However, the substitution from the online channel is relatively small. The analysis using the PSM sample yields highly consistent results as presented in Columns (7) and (8).

Table 4 reports the main effect of the second wave coupon rolling out on April 3, using the same DID approach. Here the pre-period is defined as the seven-day period before April 3 (03/27-04/02), while the post-period corresponds to the seven days since April 3 (04/03-04/09). Recall that we have two definitions of the experiment and control groups. In the first method, we define the treatment group as those who successfully obtained coupons on April 3 and the control group as those who attempted but failed to acquire coupon on the same day, without further restrictions. In the second method, we construct the treatment and control groups by sampling those who have not been treated in the first wave, in order to parcel out the potential lagged effect from the first wave. The results using each treatment/control definition are presented in Panel A and Panel B.

As shown in Column (1) of Panel A, the average treatment effect is RMB 372.6 for the unmatched sample. That is, the individuals with coupon on average spent RMB 372.6 more than their counterparts in the control group during the coupon redemption week of the second wave. Considering that government effectively subsidized RMB 63.8 per coupon in the second wave, the estimated MPC is 5.8. The higher MPC than the first wave is possibly due to the fact that the required minimum spending to redeem a voucher is higher in the second wave, which leads to a larger purchase amount. Again, we find that that the increased spending in offline purchases has negligible substitution effect of online transactions. The estimates using the PSM sample closely matches as reported in Columns (5) - (8).

The results with the alternative definition of the control group are presented in Panel B. The estimated treatment effect is RMB 385.3, which is not statistically different from that in Panel A.[17] It suggests that the group of coupon receivers in the second wave who may have received coupons in the first wave does not respond differently from the first time coupon claimers. In other words, it seems that there is little lagged effect from the previous wave coupon.

The results from both waves of the coupon program consistently suggest that the small doses of government subsidy in the magnitude of RMB 50 - 100 per person coupled with redemption threshold (minimum purchase amount) can effectively induce more spending. Consumers are highly responsive to such small-value short-duration coupon that has the nature of "use-it-or-lose-it". The estimated MPC is 3.5 – 5.8 in this study, which is much higher than the MPCs documented in the previous studies, usually in the range of 0.1-0.8. We discuss the potential explanations of this finding in the later section.

4.2 The Effect of Coupon Acquisition on Different Types of Spending

To further understand consumer response to the coupon and explore the sources of excess spending during the coupon week, we conduct the following analysis: (1) we decompose the total expenditure into categories such as catering and clothing and estimate the effect of coupon acquisition on the spending of each category; (2) we sort transactions by purchase size and analyze the effect of coupon on different levels of transaction amount.

Table 5 shows the results of the first analysis. We focus on five categories that are most relevant for offline purchases and identifiable from the transaction records, which include restaurants or catering, food and drinks, clothing, nondurables and services (excluding catering). Note that the category list does not exhaust all types of purchases. We categorize the transactions and compute the total spending in each category during the coupon week for each individual in the sample. We then conduct the DID analysis using the category level spending as the dependent variable.

Panels A and B report the category-level analysis for the first and second wave coupon respectively, using the matched samples. In both waves, we find that there is a substantial increase in expenditure on restaurants and food and drinks for the experiment group relative to the control

[17] In the following analysis of the second wave coupon, we use the first definition of the treatment/control group if not explicitly noted.

group during the coupon redemption week. The incremental consumption from these two categories is RMB 65.5 (RMB 47.8 + RMB 17.7) in Wave I and RMB 181.6 (RMB 125.8+ RMB 55.8) in Wave II, which contributes to half of the coupon effect size. In the second wave, coupon also induced a significant increase in spending on clothing and services. Our results suggest that many consumers respond to the small value coupon (e.g. "RMB 40 -10") with more spending in daily consumption such as eating and drinking, which typically involves low transaction amount. Higher coupon value in the second wave (e.g. "RMB 200 -35") incentivizes consumers to purchase items of relatively higher value such as clothes and services.

To further investigate how the variation in coupon face value affects purchase size, we exploit detailed transaction-level information and analyze transaction amount in Wave II coupon. Recall that there are three distinctive vouchers in the coupon packet, i.e., "RMB 100 -20", "RMB 200 -35" and "RMB 300 -45". We therefore classify transactions into three categories based on purchase size: (a) RMB 100 to 199.99; (b) RMB 200 to 299.99; (c) RMB 300 or above. For completeness, we also examine the purchase size below RMB 100. For each individual in the treatment and control group, we aggregate their total transaction amount in purchase size bin in each period, and conduct the DID analysis separately. The results are presented in Table 6. Compared with the control group, the treatment group on average increased their spending by RMB 71.3, RMB 123 and RMB 228.1 in purchase sizes of (a) to (c) respectively. We can roughly compute the effectiveness of each voucher by dividing the increased amount of the corresponding purchase size with the effective government subsidy. For example, the estimation result on purchase size (a) largely reflects the effect of the "RMB 100 -20" voucher. Given that the redemption rate of this voucher is 68.5 percent, which is equivalent to an effective government subsidy of RMB 13.7, the implied MPC of this voucher is 5.2 (71.3/ 13.7).[18] Similarly, the estimated MPC for voucher "RMB 200 -35" and "RMB 300 -45" are 5.7 and 8.0. The results suggest that the minimum purchase amount requirement in coupon design affects the magnitude of the coupon effect, and the effect increases with the coupon face value.

4.3 The Dynamic Effect of Coupon Issuance

The above analyses focus on the immediate effect of coupon issuance, i.e., how coupon receivers responded during the redemption week. The results from both coupon waves indicate that coupon receivers significantly increased their spending in the redemption week relative to their counterparts

[18]The caveat is that a consumer may use the lower value vouchers ("RMB 100 -20", "RMB 200 -35") in purchasing a higher price item (e.g. over RMB 300). Therefore, the increase in spending could reflect the mixed effect of different coupons.

in the control group. An important question is whether such coupon induced expenditure would crowd out consumption in the subsequent period. In other words, whether the treatment effect of coupon is due to intertemporal substitution.

To examine the hypothesis, we draw a random sample of 100,000 individuals who received coupon packets in the first wave but not the second wave and track their purchases till one week after the coupon expiration date, i.e., April 3 to April 9. The control group includes 100,000 individuals who attempted but failed to obtain coupons during the whole observation window from March 27 to April 9. We estimate the lagged effect of coupon issuance using Equation (2) and report the results in Table 7. Column (1) shows the estimates using the full sample while Column (2) uses the matched sample based on propensity score matching.

In Column (1), the estimated coefficient on the interactive term $Treat \times Post$ is 103.9, which suggests that the experiment group on average spent RMB 103.9 more than the control group during the coupon week. The estimated coefficient on the interactive term $Treat \times Post2$ is -11.1, indicating a lower level of spending by the treatment group during the post coupon week than the control group. However, this difference is statistically insignificant. It suggests that the excess spending incurred during the coupon redemption period does not significantly crowd out subsequent spending. The results in Column (2) using the matched sample are highly consistent.

Another question is whether the effectiveness of coupon in inducing excess spending wears out easily given the high frequency of coupon roll-out. Although the analysis of the second wave coupon shows a high treatment effect with an MPC of 5.8, which seems to suggest the effectiveness is sustainable in the short run, one could argue that the two waves are not directly comparable with different coupon design. However, the third wave coupon rolling out on April 10 has the exact design as the first wave, which offers an opportunity to address the question.

We first take a random sample of 100,000 individuals who acquired Wave III coupon as the experiment group and another random sample of 100,000 individuals who attempted but failed as the control group. Column (1) of Table 8 shows the DID estimation results following Equation (1). The results are qualitatively the same as the results of the first wave coupon reported in Table 3. The estimated treatment effect is about RMB 139. The redemption rate in this wave is 82.4 percent, which implies the effective government subsidy is RMB 41.2 per coupon, and the estimated MPC is 3.4, which is highly comparable with the MPC in the first wave, 3.5. This result suggests that the repeated coupon issuance does not compromise the effect in boosting consumption, at least in the short run.

Note that the individuals in the experiment group above may include both first-time coupon receivers and those who have claimed coupons multiple times. To further examine the effect of repeated treatment, we randomly draw another 100,000 individuals who successfully acquired both the Wave I and Wave III coupons to form the experiment group, and define the corresponding control group as those who received coupons in Wave I but not wave III. The DID analysis of this setting is reported in Columns (3) and (4). The estimated treatment effect is RMB 168.8, which corresponds to an MPC of 4.1.

Finally, we utilize data from another coupon wave rolling out on April 30 to double check the persistence of the effect. This wave offers a coupon packet with three "Spend RMB 40, get RMB 10 off" vouchers and the redemption rules are the same as the first wave coupon with a seven-day redemption period. Using similar sampling methods as Wave I, we identify a treatment effect of RMB 121.2. Given that the redemption rate in this wave is close to 80% with effective government subsidy of RMB 24 per coupon claimer, the estimated MPC is 5.1.

Taking the evidence together, we find that the week-long coupon program can effectively increase the spending during the redemption period and such effect is not induced by intertemporal substitution. In addition, the effect of coupon on spending persists across multiple rounds of coupon issuance. One possible reason is that the excess spending induced by coupon concentrates on high frequency daily items such as eating and drinking, as reported in the last section. Unlike purchases of durable goods, expenditure in such categories in the current period has little influence on the future spending.

5 Heterogeneity and Robustness Analysis

5.1 Heterogeneity across Consumer Groups

In this section we study how the effectiveness of the coupons in stimulating spending varies in the cross section by exploiting the fact that we observe account-holders' demographic characteristics and past transaction activities. In what follows we report the heterogeneity analysis of the first wave coupon on the matched sample. The results of the second wave coupon yield qualitatively the same conclusions and are available in the Appendix.

We first study how the general expenditure level before the program affects a consumer's responsiveness to the coupon program. We split our sample into terciles according to an individual's expenditure level, which could be considered as a proxy for one's income level. An individual falls in the low expenditure group if his average monthly expenditure during the six months before the program is below the 33.3 percentile of the distribution. The high expenditure group is defined as those with expenditure above the 66.7 percentile. We find that the coupon redemption rate is the highest among the low expenditure group at 77.8 percent and the lowest for the high expenditure group at 63.2 percent. For each tercile, we also run a separate DID analysis following Equation (1) and present the results in Columns (1) – (3) in Table 9. The estimates indicate that the low expenditure group are the most responsive to the government coupon. The coupon recipients in the low expenditure group on average spent RMB 161.7 more during the coupon redemption week, relative to their counterparts in the control group. The estimated effect size for the median and high expenditure groups are RMB 140.1 and RMB 111.1 respectively.

We next study how the purchase habit, in terms of whether one favors online or offline channels, affects his response to the coupons, which are applicable only to offline purchases in our setting. We construct an online index, which is computed as the ratio of the total amount of online transactions in the last six months relative to the total transaction amount during the same period of time. A higher ratio suggests higher tendency to use the online channel. We then classify the consumers into low, median and high groups, which corresponds to the bottom tercile, the middle tercile and the top tercile in the distribution of the online index. We find that the redemption rate is negatively correlated with the online index, i.e., the group less prone to online purchases redeemed more coupons. Columns (4)- (6) of Table 9 presents the separate DID analysis for each group. We find that the treatment effect is the most pronounced among the group with low online index. This group of consumers increased their spending by RMB 169.4 relative to the controls during the coupon week. The effect is substantially higher than the other two, which suggests that consumers who are used to offline channels for purchases (low online index) are more responsive to the coupon program.

We further utilize the account information on *Huabei*, the virtual credit card service provided by Alipay, to examine the heterogeneous effect.Whether one has access to Huabei may reflect one's need for credit. We randomly draw 10,000 accounts with Huabei and another 10,000 accounts without Huabei from the sample and estimate the treatment effect in each group.[19] The results reported in Columns (7) and (8) indicate that the estimated treatment effect of the coupons are comparable between the two groups. We further compare the effects within *Huabei* users by whether one has

[19] We use the re-sampling method to avoid revealing the ratio of *Huabei* accounts among all the users, which is considered as sensitive information from the data provider. The results are highly consistent with the unreported results using the original sample.

ever used the granted credit in transaction in the last six months, which could be an indicator of liquidity constraint. Again we randomly sample 10,000 *Huabei* accounts in each group (ever used credit or not) and estimate the treatment effect separately. We find that the consumers who have not used the granted credit before are more responsive to the coupons as evident in Columns (9) and (10). This seems to suggest that liquidity constraint is unlikely an explanation for the heterogeneity of MPCs in our setting. We defer a more careful discussion of the operative mechanisms to Section 6.1.

Finally, we analyze how different age groups respond differently to the program. Data shows coupon redemption rate increases with age. Columns (11) - (13) presents additional analysis at the age group level. The point estimates indicate that, the group of consumers aged above 40 is the most responsive. On average they spent RMB 173.6 more than the control group during the coupon week, substantially higher than the average effect RMB 131 of the age group 31-40 and RMB 111.7 of those below 30.

5.2 Robustness Checks

We perform several additional analyses to check the robustness of the results. The first concern is that the treatment group and the control group might be different along unobserved dimensions. Although the matched sample based on propensity scores shows that the two groups are nearly identical along observed characteristics and spending patterns before the program, there could exist unobserved differences which correlate with consumption tendency and bias the estimates. For example, as the coupons were distributed in the way of "first come first serve" and the starting time was publicly announced, those who arrived early and therefore successfully acquired the coupon might have a higher spending propensity and higher sensitivity to coupon than the late comers in the control group, leading to an overestimation of the treatment effect.

To test whether the timing of coupon application is correlated with the responsiveness, we split the treatment group evenly into two groups, *Early* and *Late*, based on the time of arrival in coupon application. If the argument is true, then we should see a different treatment effect across the two groups. We use the following specification.

$$y_{it} = \alpha_0 + \alpha_1 Treat_i^E + \alpha_2 Treat_t^L + \alpha_3 Post_t + \alpha_4 Treat_i^E \times Post_t + \alpha_5 Treat_i^L \times Post_t + \gamma X_{it} + \varepsilon_{it} \quad (3)$$

where $Treat_i^E$ and $Treat_i^L$ are the dummy variables indicating the early (first half) and late (second half) treatment group with coupons. The coefficients α_4 and α_5 captures how the spending of each group reacts to coupon acquisition during the redemption week, relative to the control group. If $\alpha_4 > \alpha_5$, it suggests those who applied early are more responsive to coupon and spend more.

Panel A of Table 10 reports the results using the sample from wave I. We find that the treatment effects of the *Early* group and *Late* group are of the same magnitude and the difference is statistically insignificant. It suggests that the order of arrival in coupon application is not correlated with coupon responsiveness.

Another concern is that although Alipay is the dominant mobile payment platform operative in China, especially Hangzhou, consumers may use alternative payment methods for daily transactions which are not recorded in the data. Like other research on government stimulus program that utilizes transaction level data from one financial institution (e.g., Agarwal et al., 2007; Agarwal and Qian, 2014), our transaction-level data do not exhaust all transactions by an individual in our sample. This however is not an issue if consumers' payment habit is relatively stable as the identification of the coupon effect on spending is based on the difference-in-differences approach. Still, one concern arises in the sense that consumers with coupon may shift their transactions from other payment methods, such as cash or other mobile platforms, to Alipay in order to redeem the coupon. In other words, the identified treatment effect could be the mere substitution for other payment methods.

To examine consumers' payment habits, we did an online survey in the middle of April among Hangzhou residents. The respondents include 181 females and 66 males from different age groups. 91.5 percent of the respondents reported Alipay as their primary payment method for offline transactions. It was used in 86 percent of transaction occasions on average. The high penetration rate of Alipay implies that payment substitution, if any, is not likely to be substantial in this context. 83 percent of the respondents had successfully acquired the government issued digital coupon at least once. The data seems to suggest that more frequent users of Alipay are more likely to acquire coupon. Nonetheless, we do not find significant difference across individuals that obtained coupon once, twice or three times in terms of the percentage of transaction occasions and transaction amount involving the use of Alipay. It provides some evidence that choice of payment method is relatively stable and is not affected by coupon usage.

As a further test, we run the DID analysis using data from the first wave coupon by excluding individuals with low transaction amount before the experiment. Specifically, we exclude individuals with transaction amount less than RMB 100 per month on average from September 2019 to February

2020. The idea is that low transaction volume may indicate that an individual's primary payment method is not Alipay before the experiment and payment switching is more likely to occur among this group of consumers. By excluding these individuals in both the experiment and control groups, we focus on the more frequent users of Alipay with less room for substitution. Panel B of Table 10 reports the results. We find that the estimated treatment effect using the restricted sample is RMB 125.7, which is highly consistent with that from the full sample analysis (Table 3) and the difference is statistically insignificant. It implies that substitution from other payment methods is not the main account of the increased consumption.

5.3 External Validity Check

Although we have studied multiple rounds of coupon issuance and consistently find a high MPC, our analysis is using data from the city of Hangzhou only, arguably one of the most developed areas in China where consumers have high purchasing power. One question is whether such coupon program would be effective in spurring additional spending in less developed region.

To further check the validity of the main results, we obtained data from Guangxi, an autonomous region (equivalent to province) located in South China with 49.6 million population and 14 cities. Guangxi is ranked among the bottom tier regions in China in terms of economic development. Its per capita GDP in 2019 is approximately RMB 43000 ($6200), much lower than the national average. Since late March, the regional government of Guangxi has collaborated with Alipay platform and rolled out several waves of digital coupon in an effort to spur consumption hit by the pandemic. The data we use for the analysis is from the wave rolling out on April 23. The coupon packet includes one "spend RMB 5, get RMB 1 off" voucher, five "spend RMB 25, get RMB 5 off" vouchers and two "spend RMB 100, get RMB 20 off" vouchers. All the residents in Guangxi including visitors are eligible for the coupon. The rules of coupon acquisition and redemption are quite similar to the Hangzhou coupon program as introduced in Section 2.3. One difference is that the coupons can be applied to some online transactions as well. This wave of digital coupon was released on April 23 and the coupons were valid for seven days. The overall redemption rate for the three types of vouchers "RMB 5 -1", "RMB 25-5" and "RMB 100-20" are 73%, 48% and 63% respectively. Given the redemption rate, the effective government subsidy is RMB 38 per coupon claimer.

We randomly draw 100,000 consumers who successfully acquired the coupon packet on April 23 as the treatment group, and a random sample of 100,000 consumers who attempted on April 23 but did not get coupon throughout the seven-day period as the control group, and perform propensity score matching to get a more comparable sample. We estimate the effect of coupon acquisition on consumption during the redemption week using the same DID method as in Equation (1). In this case, the pre-period refers to the seven days prior April 23 (from April 16 to April 22) and the post-period refers to the coupon redemption week (from April 23 to April 29). Since the consumers are from 14 different cities, we also control for city fixed effect in the regression. Table 11 reports the estimation results on the matched sample. We find that consumers in the treatment group on average spent RMB 197.4 more than the control group during the period of coupon redemption, as the interaction term shows in Column (1). The decomposition of the total consumption in Columns (3) and (4) indicate that the increase in spending is mostly driven by offline purchases, while the increase in online purchase is quite small in magnitude.

Given the fact that the effective average government subsidy is RMB 38 per person, the RMB 197.4 increase in spending then implies a MPC of 5.2. The estimated elasticity is 10.9, derived from the results in Column (2). These results provide strong evidence that the digital program is also effective in driving additional consumption in less developed regions.

6 Why was the MPC so high?

6.1 Standard Neoclassical Models

The MPCs in our study, ranging from 3.5 to 5.8, pose a challenge to standard explanations. First, our estimation is not consistent with the life cycle/permanent income (LCPI) model. According to the LCPI theory, these coupons are too small in size and should have inconsequential effect on spending because such windfalls constitute meaningless changes to lifetime wealth. Even if consumers were surprised by the receipts of the coupon, as the chance to successfully acquire the coupon is about 20 percent in each round given the limited supply, our estimated responses are large enough to reject the LCPI model, which predicts that households should consume at most the annuitized value of a transitory increase in income (see, e.g., Parker et al., 2013).

An alternative mechanism that may explain our empirical findings, especially the heterogeneity of MPCs, is liquidity constraints. Agarwal et al. (2007) examine households' responses to the 2001 tax rebates using credit card account information, and document that spending rose most for consumers who were most likely to be liquidity constrained, whereas debt declined most (so saving rose most) for unconstrained consumers. Agarwal and Qian (2014) study unanticipated income shocks in Singapore and find that households, which are more likely to be liquidity constrained, are more responsive to the cash payments. However, liquidity constraint alone is not a competing model to the LCPI model and there is still no consensus about the actual importance of liquidity constraints in explaining consumers' responses to fiscal transfer payments. More importantly, our findings are in contrast with the predictions of the liquidity constraint hypothesis. First, unlike tax rebate or cash payment, the digital coupon does not offer recipients the option to save or to spend due to the "use it or lose it" feature of the design. The coupon recipients have to spend in order to gain from the government subsidy, which incurs expenditure out of their own pocket. Although we do find that consumers from the low income (low expenditure) group spend more than those from the high income (high expenditure) group with coupon (see Columns (1) - (3) of Table 9), it should not be interpreted as evidence supporting the liquidity constraint hypothesis.

Second, we have studied the differential responses to the receipts of the coupons by individuals with access to Huabei, a virtual credit card offered by Alipay. Consumers, who have Huabei credit lines but have never used any credit, are presumably less liquidity constrained than those who have used Huabei's credit before. However, the results as reported in Column (9) and Column (10) of Table 9 indicate that the former group is more responsive to the coupons than the latter, which is inconsistent with the prediction of the liquidity constraint hypothesis. And finally, the coupons in our setting are inconsequential in amount and can hardly ease the liquidity constraints, if any.

6.2 A Behavioral Model with Mental Accounting and Loss Framing

Browning and Crossley (2001) suggest that when transfer payments are large and predictable, the MPC should be relatively small. Studying the consumption response to annual payments from the Alaska Permanent Fund, Hsieh (2003) finds a MPC of zero. He attributes such low response to the large and predictable payments from the Alaska Permanent Fund. The coupon program in our setting is exactly the opposite of the Alaska Fund Payments in both respects – the payments are small and uncertain.[20] We speculate that the higher MPCs are associated with the design of the coupon program and its implementation in the field. We turn to behavioral factors to investigate the potential mechanisms operative.

One potential behavioral factor that may accommodate our empirical findings is mental accounting. According to the theory of mental accounting, people group their financial resources and

[20] The government payments in our setting are uncertain for two reasons. First, an individual has to apply for the coupons on a "first-come-first serve" basis; second, he needs to spend out of his own pocket in order to lock in the government payment, i.e., "use-it-or-lose-it".

expenditures into "mental accounts" and make decisions within the context of those narrowly defined accounts instead of integrating all decisions together in a single optimization problem (Shefrin and Thaler, 1981; Thaler, 1985, 1999).

The mental accounting operation suggests that consumers in our setting treat the digital coupon as part of a separate account – that is, income is non-fungible in the sense that it is divided into categories (e.g., regular weekly budget vs. coupon-related income account) and consumers spend within the budget. The coupon account involves small windfall, and a consumer may use this unexpected income to purchase items he would not purchase otherwise (Milkman and Beshears, 2009). This is consistent with our finding that coupons generate excess spending among the treatment group relative to the control group.

As a further test of the null hypothesis of fungibility motivated by mental accounting, that it, consumers treat government payment in the form of digital coupon as fungible with other income (e.g., their weekly budget), we examine the distribution of the consumers' purchase size. If the digital coupon is fungible (i.e., money in the coupon-related expenditure account will be spent just as well as in another), the distribution of the treatment group's purchase size should not be significantly different from that of the control group, as the coupon can be applied to any transaction above the minimum requirement (e.g. RMB 40). The top two panels of Figure 4 present the histogram of the purchase size for the treatment and control groups in Wave I respectively. It is highly noticeable that the purchase size of the treated consumers clusters at RMB 40, while we do not find the same pattern for the control group. The bottom panel of Figure 4 depicts the kernel distribution of the two groups. The Kolmogorov-Smirnov test rejects the null hypothesis that the two distributions are equal.

We conduct the same analysis for Wave II. The histogram of the purchase size by the treatment and control group is presented in Figure 5. We find that the purchase size of the treatment group concentrates at RMB 100, RMB 200, and RMB 300 respectively. We do not observe the same pattern for the control group. The two distributions are significantly different according to the Kolmogorov-Smirnov test.

Nonetheless, mental accounting alone cannot fully rationalize an estimated MPC ranging from 3.5 to 5.8. We speculate that the MPCs in our setting, an order of magnitude larger than those in previous studies, have a lot to do with the coupon program's several salient features. These distinctive features are built on behavioral insights that influence behavior, among which loss framing generates a first-order effect.[21] One of the salient features of the digital coupon is its nature of "use-it-or-lose-it". The coupon subsidy is not cash equivalent and it cannot be captured unless the spending reaches a certain amount. Take the coupons issued on March 27th as an example. "Spend RMB 40, get RMB 10 off" suggests that if spending is less than RMB 40, the coupon holders would lose the 'endowed' RMB10 of government subsidy. The tendency to avoid loss, i.e., the government subsidy, incentivizes coupon holders to spend.[22]

Loss aversion emerges from a behavioral model with reference-dependent preference (Kahneman and Tversky, 1979).[23] The implementation of the coupon rollout, that consumers have to compete for limited supply of the coupons (albeit in large quantity), further amplifies loss aversion. The scarcity effect (Cialdini, 1993) may enhance the perceived value of the coupons among those who have successfully acquired.

Notably, the loss framing effect alone cannot explain the high MPCs either. In the absence of mental accounting, the coupon subsidy could be fungible with other source of income and coupon-induced spending may well substitute for consumers' regular weekly expenditure, in which case we would fail to see coupon holders spend significantly more than the non-holders. Mental accounting and loss framing are two primary mechanisms driving higher MPCs in our study.

There are other behavioral factors that may contribute to the high MPCs of the digital coupon. First, by naming the vouchers as "consumption coupon" (a direct translation from Chinese), it highlights spending as the stated goal of the government subsidy and helps to enhance MPC. This can be considered as a sort of framing or labeling effect (Beatty et al., 2014). In addition, the short duration of the coupon redemption period reinforces urgency to spend and reduces void coupons due to procrastination. Finally, the rollout of the digital coupons is promoted as a way to support local business on news media, which may trigger other psychological responses such as reciprocity (Rabin, 1993) that enhance the effectiveness of the coupon program.

6.3 Behavioral Explanation for the Heterogeneity in MPCs

Having established mental accounting and loss framing as the two primary mechanisms driving high MPCs in our setting, we conjecture that the effectiveness of the government payment program is a

[21] See Dellavigna (2009) for a survey on the literature of behavioral economics.

[22] The loss framing effect, in our setting, is equivalent to the endowment effect that individuals have a much higher reservation price for an object they own than their willingness to pay for it when they do not own it.

[23] There are many examples of the loss aversion effect in both the laboratory and field experiments. See, for example, Odean (1998); Kahneman et al. (1990); List (2003). Fryer et al. (2018) document the evidence of the loss aversion effect in the design of teacher incentives to improve their impact on student performance.

function of the consumers' awareness of these behavioral biases and whether they learn to counteract with the biases. Results from List (2003)'s field experimental study show that consumers who are more experienced in the market can hone their behavioral rules and are therefore less subject to the influence of behavioral biases, implying that more experienced consumers may be less responsive to the coupon program. Mani et al. (2013) conduct both laboratory and field experiments and identify a causal relationship between poverty and cognitive ability. The implication for our research is that low income consumers may be more subject to behavioral biases and are therefore more responsive to coupons.

We utilize the transaction-level data on consumers' coupon redemption decisions and investigate how consumers' redemption rate and coupon-induced spending vary across variables that are reflective of a consumer's market experiences and cognitive ability. As discussed in Section 5.1, we find that low income consumers, consumers with less online shopping experiences and consumers in older age group report higher redemption rate and higher coupon effect size than other consumer groups. These consumers arguably are less experienced with digital coupons and are more subject to the influence of behavioral factors. As a result, the treatment effect tends to be larger for consumers with such attributes. While there could be alternative explanations for the heterogeneous responses to the digital coupons, these results are consistent with the behavioral account.

On a related point, we interviewed the policy makers who were involved in the design of the coupon program. The narrative evidence shows that when planning the coupon program, the policy maker intentionally chose small value, short duration, and in the early field trials, an alternate issuance of two different types of coupon packets. These features of the program suggest that the coupon claimers do not have long enough time and strong enough motive to adjust their cognitive biases. As such, the Chinese digital coupon program presents an interesting case example of embedding insights from behavioral models into the design and implementation of novel policy tools.

7 Further Discussion and Policy Implications

Our proceeding analysis shows that the digital coupon program has a larger economic effect when people are more subject to behavioral biases. A public policy built on people's behavioral biases, despite its effectiveness, invites a debate on whether a policy should try to de-bias people to get them to make more rational decisions rather than develop behavioral influences into the policy design and implementation. While we avoid addressing this question at a broad level, we emphasize the importance of the setting and the intended goals of the policy. In our setting, the excess spending induced by the coupons, as a result of consumers' behavioral biases, largely falls into small businesses and in particular catering and lodging services. It has important implications for the local commerce and economy. The statistics report that the total sales of catering and lodging businesses in China decreased by 44.3 percent in the first quarter of 2020, due to the COVID-19 pandemic. This sector alone absorbs 29.45 million employment in 2019.[24] The coupon program alleviates the severe difficulties faced by the small businesses by spurring consumption. Moreover, there could be indirect effects from the program that benefit the entire local economy as consumers resume their shopping trips. As such, from the perspective of welfare analysis, the behavioral biases embedded in the design of the coupon program in fact engage consumers to make choices that benefit the society as a whole.

It is of particular policy interest to discuss the aggregate effect of rolling out the coupon program at the national level. Despite that many aspects of the Hangzhou coupon program (i.e., small face value with minimum spending requirement, short duration, multi-wave disbursement using mobile payment platform, etc.) have been followed by many Chinese cities, our evaluation of the effects of this program is highly localized. Policy treatments may interact with characteristics of the policy setting including the severity of economic damage caused by COVID-19, the target population, their income level, the penetration rate of mobile payments, size of the local stimulus program, and other contextual factors – policies that work in one place may not apply to other places. Predicting an aggregate effect of the coupon program, if scaled nationwide, unavoidably faces the challenge of external validity (Ludwig et al., 2011; Banerjee et al., 2017). Note that the aggregate effect is a function not only of the recipients' MPCs, but also of whether the program is scalable. Our study has little to say about the two related things.

The concern about external validity however could be alleviated due to the following reason. Field experiments of the coupon program in a handful cities provide earlier results that issuing digital coupons can potentially be used as an effective policy intervention to instill confidence among consumers and stimulate consumption. The effect of the coupon program on consumption can be accurately and timely assessed which allow the policy makers to target the most responsive consumers. The small value, short duration coupon can be repeatedly issued without a substantial diminishing effect on the recipients' spending. The field experiment benefits from iterative design,

[24]The data are extracted from the website of the National Bureau of Statistics of China: http://www.stats.gov.cn.

testing and refinement which improve the coupon usage and the effects on participating local merchants.

China now boasts of more than 1 billion mobile payment accounts, and more than 300 prefecture-level municipal cities. If the digital coupon program as the one in Hangzhou can be scaled nationwide in the next 6-12 months, and each account holder, through many rounds of coupon rollouts, redeems an average of RMB 500 (US$70.7) worth of coupons, then RMB 500 billion (about 0.5 percent of China's GDP in 2019) of government payment can generate RMB 1.75 trillion of excess spending which increases retail sales by 4.25 percentage points.[25] If we assume that retail growth rate is about the same as that of consumption, then a 4.25 percentage points growth in retail sales translates into a 2.46 percentage increase in output.[26] Our back-of-the-envelope-calculation suggests a sizeable aggregate effect on output.

Our analysis on the aggregate effect of the coupon program is of course suggestive. It does not consider the general equilibrium effects that could have amplified or diminished the initial spending impulse. In addition, the program may have large and positive effects on the entire local economy rather than only the treated. However, with data at hand, we are unable to estimate the indirect effects. Our partial equilibrium estimates of the policy's economic magnitude may be biased.

Duflo (2017) advocates that to achieve desirable results, policy implementations need to have many details taken care. While theoretical models normally fail to provide much guidance on good policy implementation, field experimentation is an extremely useful tool to fix critical policy details. In our setting, by breaking a usually one-time and large scale nation-wide program into many localized programs, the policy makers and economists can better evaluate the first-order impacts of those critical policy details - most of which are intertwined with the characteristics of local setting – and pursue good policy implementation. In the current economic recession, governments are in an urgent need to put forward cost effective policies to recover the economy. The experimental implementations of the digital coupon program provide some useful implications for policy making.

8 Conclusion

This paper studies a large-scale digital coupon program by local government in China to stimulate consumption in the pandemic. Our analysis of multiple waves of the digital coupon program utilizing a rich panel of transaction-level data of more than 1 million individuals yield several

[25] Here we assume that the MPC is 3.5.

[26] $2.46 = 4.25 \times 0.578$. Note that in 2019, consumption drove 57.8 percent of GDP growth in China.

notable findings: (1) Consumers are highly responsive to the small-value short-duration coupon issued by the government. The MPC is surprisingly high ranging from 3.4 to 5.8 in this study, an order of magnitude larger than those reported in previous studies. We resort to behavioral theories, in particular mental accounting and loss framing, to explain this finding. (2) The increase in consumption during a coupon redemption week does not negatively affect future spending and the effectiveness of coupon does not wear out over waves of issuance. The incremental consumption induced by the coupons largely falls in everyday purchases such as food and catering. (3) There is substantial heterogeneity in coupon responsiveness across different consumer groups and different coupon designs, which suggests that targeted distribution and change of design can potentially increase the effectiveness of such tools.

Our research has important policy implications. It suggests that a well-designed coupon program can be a useful policy tool to stimulate consumption, which complements the usual stimulus programs such as cash payment and tax cut in response to economic downturn. The experimentation of such program is particularly relevant when governments are in an urgent need to bring forward cost effective policies to recover the economy. We find the small-value coupons directly benefit the local small businesses which have attracted a high proportion of coupon redemption. When extrapolating the results to the national level, our calculation indicates a digital program of RMB 500 billion covering 1 billion mobile payment account holders can increases retail sales by 4.25 percentage points in the country. Although the estimation is with caveats, our analysis suggests that multi-round localized policy interventions may achieve better policy goals than the usual one-time, blanket stimulus program.

Finally, our research sheds light on the broader discussion of policy design integrated with behavioral insights. The high effectiveness of the digital coupons as documented is closely related to the design and implementation of the program, which invokes several behavioral mechanisms of human behavior. Future research is needed to fully understand the underlying mechanisms and potentially decompose the overall effect. The behavioral insights, coupled with digital technology which enables real-time tracking and evaluation, offer prominent opportunities to explore more effective public policy tools.

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Table 1. Summary Statistics

This table shows the summary statistics of the treatment group and control group. Panel A reports the statistics of the sample for Wave I coupon. Panel B and Panel C report the statistics for the two samples for Wave II, respectively. Every panel includes the statistics of the sample before and after matching. *Gender* is a dummy that equals one for male and zero for female. $Offline\,spending\,in\,March$ means the total offline spending in March (from March 1 to March 19), and $Monthly\,offline\,spending$ means the average monthly offline spending over the six months before the program (from September 2019 to February 2020). The unit of spending is in RMB yuan. T-test is used to compare the group means of the treatment and control group of each variable.

	Treatment Group		Control Group		p-value of
	Mean	SD	Mean	SD	t-test
Panel A: Wave I					
Before Matching					
Gender	0.454	0.498	0.562	0.496	0.000
Offline spending in March	1,900.486	5,316.139	1,667.903	5,179.382	0.000
Monthly offline spending	4,259.144	6,686.134	3,630.633	6,937.970	0.000
Obs.	100,000		100,000		
After Matching					
Gender	0.512	0.500	0.516	0.500	0.138
Offline spending in March	1,784.817	5,048.531	1,831.927	5,413.319	0.095
Monthly offline spending	3,928.311	6,386.982	4,005.897	7,138.816	0.034
Obs.	68874		68874		
Panel B: Wave II- Sample 1					
Before Matching					
Gender	0.429	0.495	0.505	0.500	0.000
Offline spending in March	1,923.822	5,514.433	1,716.526	5,095.157	0.000
Monthly offline spending	4,182.255	6,934.683	3,785.158	6,478.481	0.000
Obs.	100,000		100,000		
After Matching					
Gender	0.471	0.499	0.471	0.499	1.000
Offline spending in March	1,726.192	4,960.700	1,723.865	5,036.932	0.927
Monthly offline spending	3,800.471	6,286.476	3,819.727	6,428.028	0.554
Obs.	76,466		76,466		
Panel C: Wave II- Sample 2					
Before Matching					
Gender	0.512	0.500	0.555	0.497	0.000
Offline spending in March	1,645.261	5,093.779	1,603.141	5,068.113	0.064
Monthly offline spending	3,535.609	6,762.881	3,381.704	6,735.796	0.000
Obs.	100,000		100,000		
After Matching					
Gender	0.545	0.498	0.541	0.498	0.114
Offline spending in March	1,569.154	4,946.001	1,586.725	5,035.908	0.489
Monthly offline spending	3,313.239	6,572.661	3,321.461	6,687.246	0.807
Obs.	77,422		77,422		

Table 2. Summary of Coupon Redemption

This table summarizes the coupon redemption of Wave I, II and III. The upper panel shows the distribution of coupon claimers that redeemed 0, 1, 2,..., 5 vouchers in Wave I or Wave III, along with the average number of vouchers redeemed and the average government subsidy per coupon claimer. Each voucher is a "RMB40-10" type. The lower panel reports the coupon redemption rate of Wave II, which contains three types of coupon—RMB100-20, RMB200-35 and RMB300-45, and the average government subsidy per coupon claimer.

Number of Coupon Redeemed	Percentage of Coupon Claimers(%)	
	(1)	(2)
	3/27 Wave I	4/10 Wave III
0	11.7	5.0
1	8.1	4.1
2	9.5	6.2
3	8.9	7.9
4	11.8	12.6
5	49.9	64.3
Average Number Redeemed	3.5	4.1
Average Government Subsidy (RMB)	35.1	41.2
Coupon Type	4/3 Wave II Redemption Rate (%)	
100-20	68.5	
200-35	61.4	
300-45	63.5	
Average Government Subsidy (RMB)	63.8	

Table 3. The Average Effect on Spending— Wave I

This table shows the DID results of Wave I coupon. The dependent variables include total spending ($Payamt$), the log transformation of the total spending $log(1 + Payamt)$, the offline spending ($Offpayamt$) and the online spending ($Onpayamt$) in a period at individual level. Columns(1)-(4) are baseline DID results using the full sample, and Columns(5)-(8) are the results using the PSM sample. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample				PSM Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Payamt	log(1+Payamt)	Offpayamt	Onpayamt	Payamt	log(1+Payamt)	Offpayamt	Onpayamt
Treat x Post	12,464.380***	0.762***	14,553.120***	-2,342.192***	13,372.580***	0.921***	14,127.720***	-1,182.390***
	(888.192)	(0.014)	(639.475)	(300.298)	(1,071.415)	(0.017)	(770.197)	(362.502)
Treat	931.611	0.465***	-1,131.194*	3,811.373***	-765.382	0.291***	17.027	90.312
	(784.341)	(0.012)	(586.683)	(307.666)	(911.498)	(0.015)	(677.364)	(357.142)
Post	-1,138.626*	0.095***	755.695*	-1,723.784***	-1,865.836**	0.052***	488.610	-2,096.731***
	(611.138)	(0.011)	(441.759)	(202.863)	(771.309)	(0.013)	(554.060)	(260.387)
Age	-110.570	-0.034***	1,315.736***	-634.253***	-29.164	-0.036***	1,479.460***	-717.339***
	(172.050)	(0.003)	(132.558)	(69.876)	(205.350)	(0.004)	(160.781)	(82.147)
Age2	-2.608	0.0003***	-10.687***	-1.387	-3.631	0.0003***	-12.415***	-0.644
	(2.187)	(0.00004)	(1.717)	(0.871)	(2.615)	(0.00005)	(2.090)	(1.021)
Gender	4,984.395***	0.026***	14,409.530***	-10,644.580***	5,473.750***	0.043***	14,096.080***	-9,786.088***
	(612.942)	(0.009)	(464.594)	(251.976)	(732.496)	(0.011)	(554.722)	(299.870)
Payamt_3up	0.073***		0.040***	0.017***	0.074***		0.041***	0.017***
	(0.002)		(0.001)	(0.001)	(0.002)		(0.002)	(0.001)
Payamt_6m	0.089***		0.051***	0.023***	0.088***		0.051***	0.022***
	(0.001)		(0.001)	(0.0004)	(0.002)		(0.001)	(0.001)
log(1+Payamt_3up)		0.464***				0.449***		
		(0.003)				(0.004)		
log(1+Payamt_6m)		0.362***				0.373***		
		(0.004)				(0.006)		
Constant	25,590.810***	0.421***	-29,585.610***	44,923.290***	26,085.960***	0.603***	-32,531.790***	48,551.800***
	(2,977.548)	(0.060)	(2,237.926)	(1,244.877)	(3,530.320)	(0.074)	(2,678.410)	(1,460.922)
Obs.	400,000	400,000	400,000	400,000	275,496	275,496	275,496	275,496
Adj.R^2	0.324	0.510	0.218	0.181	0.315	0.432	0.215	0.171
MPC	3.5	–	4.1	-0.7	3.8	–	4.0	-0.3
Elasticity	–	3.0	–	–	–	3.7	–	–

Table 4. The Average Effect on Spending— Wave II

This table shows the DID results of Wave II coupon. Panel A reports the results using the first definition of the experiment and control group, while Panel B reports the results using the second definition (with restriction). The dependent variables include total spending (*Payamt*), the log transformation of the total spending $log(1 + Payamt)$, the offline spending ($Offpayamt$) and the online spending (*Onpayamt*) in a period at individual level. Columns(1)-(4) are baseline DID results using the full sample, and Columns(5)-(8) are the results using the PSM sample. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Treatment/Control Design I								
	Full Sample				PSM Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Payamt	log(1+Payamt)	Offpayamt	Onpayamt	Payamt	log(1+Payamt)	Offpayamt	Onpayamt
Treat x Post	37,263.840***	1.105***	38,798.470***	-1,198.595***	37,296.310***	1.211***	38,690.670***	-1,055.464***
	(876.473)	(0.013)	(655.791)	(269.603)	(987.675)	(0.015)	(738.869)	(304.176)
Treat	6,105.498***	0.471***	5,746.848***	624.017**	5,868.256***	0.415***	5,746.458***	13.696
	(738.997)	(0.011)	(563.469)	(265.235)	(821.609)	(0.013)	(627.693)	(293.801)
Post	-1,133.237*	-0.238***	-546.219	-280.054	-920.204	-0.249***	-593.096	-195.866
	(603.148)	(0.010)	(448.597)	(187.000)	(694.390)	(0.011)	(517.281)	(215.591)
Age	599.328***	-0.021***	1,735.869***	-494.230***	591.968***	-0.021***	1,874.662***	-664.356***
	(173.960)	(0.003)	(135.775)	(62.627)	(193.491)	(0.003)	(149.604)	(69.134)
Age2	-9.114***	0.0002***	-14.194***	-2.777***	-8.795***	0.0002***	-15.868***	-0.534
	(2.216)	(0.00004)	(1.747)	(0.776)	(2.467)	(0.00005)	(1.929)	(0.856)
Gender	8,766.232***	-0.016*	14,966.440***	-8,028.829***	8,799.551***	0.006	14,700.980***	-7,437.388***
	(619.096)	(0.009)	(493.636)	(222.473)	(673.277)	(0.010)	(528.940)	(246.494)
Payamt_3up	0.067***		0.041***	0.013***	0.070***		0.042***	0.013***
	(0.002)		(0.001)	(0.001)	(0.002)		(0.002)	(0.001)
Payamt_6m	0.092***		0.059***	0.019***	0.092***		0.059***	0.019***
	(0.001)		(0.001)	(0.0004)	(0.001)		(0.001)	(0.0005)
log(1+Payamt_3up)		0.348***				0.345***		
		(0.003)				(0.004)		
log(1+Payamt_6m)		0.352***				0.333***		
		(0.004)				(0.005)		
Constant	11,279.330***	2.133***	-37,549.190***	41,330.150***	10,757.640***	2.409***	-39,669.720***	43,553.050***
	(3,048.013)	(0.061)	(2,325.164)	(1,138.730)	(3,402.629)	(0.069)	(2,578.800)	(1,262.308)
Obs.	400,000	400,000	400,000	400,000	305,864	305,864	305,864	305,864
Adj.R^2	0.318	0.439	0.243	0.153	0.307	0.415	0.233	0.153
MPC	5.8	–	6.1	-0.2	5.8	–	6.1	-0.2
Elasticity	–	6.6	–	–	–	7.3	–	–

Panel B: Treatment/Control Design 2								
	Full Sample				PSM Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Payamt	log(1+Payamt)	Offpayamt	Onpayamt	Payamt	log(1+Payamt)	Offpayamt	Onpayamt
Treat x Post	38,534.070***	2.007***	38,532.190***	-160.032	37,940.740***	2.116***	37,734.840***	-36.261
	(787.024)	(0.017)	(616.065)	(205.584)	(874.447)	(0.020)	(687.777)	(226.063)
Treat	-971.778	0.138***	-958.408*	631.412***	-748.566	0.111***	-485.927	106.225
	(671.515)	(0.014)	(533.364)	(212.557)	(743.366)	(593.723)	(231.793)	(0.016)
Post	6,496.256***	0.251***	7,421.002***	-413.657***	6,917.180***	0.259***	7,696.740***	-374.305**
	(552.176)	(0.011)	(426.283)	(144.460)	(617.944)	(0.013)	(479.457)	(160.519)
Age	478.280***	-0.034***	1,528.917***	-665.604***	550.561***	-0.036***	1,570.601***	-751.640***
	(141.471)	(0.003)	(116.434)	(45.062)	(152.956)	(0.004)	(126.820)	(47.693)
Age2	-7.894***	0.0002***	-13.228***	0.712	-8.539***	0.0002***	-13.711***	1.909***
	(1.784)	(0.00004)	(1.486)	(0.549)	(1.928)	(0.00005)	(1.618)	(0.578)
Gender	9,038.167***	0.076***	13,951.730***	-5,877.576***	8,704.017***	0.122***	12,957.700***	-4,989.262***
	(548.381)	(0.011)	(446.807)	(183.039)	(607.496)	(0.013)	(497.761)	(199.601)
Payamt_3up	0.076***		0.049***	0.011***	0.077***		0.052***	0.011***
	(0.002)		(0.002)	(0.0005)	(0.002)		(0.002)	(0.001)
Payamt_6m	0.091***		0.061***	0.016***	0.092***		0.064***	0.015***
	(0.001)		(0.001)	(0.0004)	(0.002)		(0.001)	(0.0004)
log(1+Payamt_3up)		0.390***				0.389***		
		(0.003)				(0.003)		
log(1+Payamt_6m)		0.293***				0.279***		
		(0.003)				(0.003)		
Constant	3,803.925	1.909***	-39,292.990***	38,639.570***	1,200.458	2.093***	-40,845.630***	39,623.460***
	(2,546.282)	(0.062)	(2,054.500)	(856.768)	(2,780.232)	(0.069)	(2,262.133)	(921.643)
Obs.	400,000	400,000	400,000	400,000	309,688	309,688	309,688	309,688
Adj.R^2	0.351	0.451	0.277	0.161	0.354	0.451	0.287	0.153
MPC	6.0	–	6.0	0.0	5.9	–	5.9	0.0
Elasticity	–	12.0	–	–	–	12.7	–	–

Table 5. Cross-category Analysis

This table shows the DID results when decomposing the total expense into categories. Panel A and Panel B report the results for Wave I and Wave II, respectively. *Restaurant*, *Food*, *Dress*, *Nondurable* and *OtherService* represent restaurant and catering, food and drinks, clothes and dressing, nondurable goods and services (excluding catering service). The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 3/27 Wave I					
	(1)	(2)	(3)	(4)	(5)
	Restaurant	Food	Dress	Nondurable	Other Service
Treat x Post	4,779.570***	1,770.242***	211.996***	74.913***	450.457*
	(249.256)	(46.477)	(72.229)	(9.316)	(233.212)
Treat	380.655*	579.459***	194.570***	16.096**	−859.162***
	(223.817)	(46.797)	(67.717)	(7.097)	(203.683)
Post	−3.995	−61.305**	−1,051.434***	−25.765***	−316.311*
	(178.762)	(30.058)	(50.335)	(6.259)	(168.786)
Constant	28,594.520***	−4,248.958***	6,325.677***	−32.979	10,489.540***
	(946.082)	(218.307)	(253.522)	(28.415)	(809.133)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	275,496	275,496	275,496	275,496	275,496
Adj.R^2	0.166	0.072	0.071	0.007	0.120
Panel B: 4/3 Wave II					
	(1)	(2)	(3)	(4)	(5)
	Restaurant	Food	Dress	Nondurable	Other Service
Treat x Post	12,575.720***	5,584.266***	2,135.573***	72.798***	2,151.855***
	(242.365)	(67.776)	(74.493)	(10.490)	(208.033)
Treat	1,917.019***	993.402***	298.118***	32.334***	−190.278
	(199.993)	(55.237)	(56.125)	(8.177)	(175.747)
Post	−800.796***	−764.870***	500.062***	−20.546***	−79.893
	(162.906)	(35.873)	(47.290)	(7.038)	(145.574)
Constant	25,388.890***	−6,992.236***	4,478.446***	19.374	10,388.130***
	(917.564)	(283.948)	(256.992)	(34.070)	(716.594)
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	305,864	305,864	305,864	305,864	305,864
Adj.R^2	0.161	0.089	0.063	0.008	0.112

Table 6. Different Purchase Size Analysis— Wave II

This table shows the DID results of purchase sizes analysis of Wave II based on the matched sample. Wave II has three vouchers, RMB 100-20, RMB 200-35, RMB 300-45. We therefore classify transactions into four categories based on purchase size: below RMB 100, RMB 100-199.99, RMB 200-299.99 and RMB 300 or above. The dependent variable is the total amount of transactions in each purchase size category. MPC is calculated as the incremental spending in a purchase size by the treatment group divided by the corresponding coupon subsidy. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	$\leq$ 99.99	100-199.99	200-299.99	$\geq$ 300
Treat x Post	$-5{,}379.402^{***}$	$7{,}126.650^{***}$	$12{,}296.170^{***}$	$22{,}814.400^{***}$
	(95.079)	(95.011)	(94.013)	(947.734)
Treat	$4{,}432.696^{***}$	416.566^{***}	206.516^{***}	809.390
	(105.395)	(80.630)	(68.708)	(778.654)
Post	$-5{,}062.589^{***}$	82.624	527.782^{***}	$3{,}436.713^{***}$
	(67.010)	(65.842)	(61.203)	(664.950)
Constant	$32{,}333.370^{***}$	$2{,}977.647^{***}$	$-3{,}090.849^{***}$	$-22{,}558.450^{***}$
	(504.780)	(341.249)	(295.288)	(3,153.115)
Controls	Yes	Yes	Yes	Yes
Obs.	305,864	305,864	305,864	305,864
Adj.R^2	0.150	0.133	0.181	0.255
MPC	–	5.2	5.7	8.0

Table 7. The Lagged Effect Estimation— Wave I

This table reports the results of the lag effect test for the first wave coupon. The baseline period is one week before the coupon issuance day. *Post*1 represents the coupon redemption week and *Post*2 is the period following *Post*1 , i.e., the week after the coupon expiration date. We conduct the DID analysis on both the full sample and the PSM sample. Individual fixed effects are controlled. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Full Sample	(2) PSM Sample
Treat x Post1	10,388.050***	11,344.320***
	(1,072.081)	(1,287.656)
Treat x Post2	-1,108.379	-655.046
	(1,111.126)	(1,338.699)
Post1	-918.721	-987.975
	(736.508)	(930.601)
Post2	350.264	483.792
	(766.683)	(967.205)
Individual FE	Yes	Yes
Obs.	600,000	416,478
Adj.R^2	0.526	0.530

Table 8. Analysis of Repeated Coupon Issuance

This table reports the DID results of the April 10(Wave III) coupon and April 30 (4/30) coupon, which share the same design as the first wave coupon rolled out on March 27. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	4/10-Sample 1		4/10-Sample 2		4/30	
	(1)	(2)	(3)	(4)	(5)	(6)
	Payamt	log(1+Payamt)	Payamt	log(1+Payamt)	Payamt	log(1+Payamt)
Treat x Post	13,897.370***	1.328***	16,881.720***	0.835***	12,122.430***	1.103***
	(896.644)	(0.014)	(965.036)	(0.011)	(962.873)	(0.014)
Treat	4,818.941***	0.309***	1,797.557**	0.157***	−329.011	0.366***
	(778.356)	(0.012)	(814.237)	(0.009)	(841.376)	(0.013)
Post	-12,228.660***	-0.867***	-11,846.180***	-0.493***	5,602.359***	0.039***
	(624.757)	(0.011)	(685.342)	(0.009)	(675.834)	(0.010)
Constant	15,106.930***	3.284***	28,887.420***	3.341***	6,966.147**	2.207***
	(3,032.282)	(0.064)	(3,566.315)	(0.078)	(3,119.352)	(0.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	400,000	400,000	400,000	400,000	400,000	400,000
Adj.R^2	0.317	0.337	0.255	0.222	0.307	0.391
MPC	3.4	–	4.1	–	5.1	–
Elasticity	–	5.3	–	3.3	–	4.4

Table 9. Heterogeneous Effect Analysis—Wave I

This table shows the heterogeneous responses by consumer groups to the coupon program based on data from Wave I. The dependent variable is the total spending of an individual in a period. Consumers are divided into three groups based on their average monthly spending and online purchase ratio (online spending divided by the total spending). They are also divided by whether having *Huabei* (the virtual credit card), and whether using the credit granted if they have Huabei. We also consider three age groups, i.e., 30 or below, between 31 and 40, and 40 or above. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Monthly Spending Terciles			Online Ratio Terciles		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Mid	High	Low	Mid	High
Treat x Post	16,174.740***	14,006.760***	11,109.860***	16,940.130***	10,478.030***	12,657.190***
	(972.391)	(1,403.355)	(2,566.123)	(2,231.748)	(1,871.038)	(1,620.416)
Treat	622.194	1,112.276	-7,065.114***	-2,280.607	68.706	-1,617.699
	(770.598)	(1,112.995)	(2,226.981)	(1,983.895)	(1,536.204)	(1,343.213)
Post	-993.063	-3,839.233***	-840.405	1,848.604	302.128	-6,952.543***
	(618.990)	(1,029.082)	(1,915.320)	(1,624.163)	(1,394.948)	(1,124.124)
Constant	4,118.319	19,296.630***	51,322.590***	280.221	26,585.770***	17,083.620***
	(2,910.961)	(4,558.119)	(12,450.030)	(10,034.060)	(6,373.368)	(4,909.569)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	80,916	96,668	97,912	81,638	92,360	95,974
Adj.R^2	0.058	0.035	0.278	0.337	0.322	0.254

	Huabei		Credit Usage		Age Group		
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Yes	No	Use	No use	≤ 30	31-40	≥ 41
Treat x Post	12,232.720***	12,572.390***	11,552.590***	15,830.650***	11,169.720***	13,104.490***	17,355.880***
	(4,061.576)	(3,107.372)	(4,136.930)	(3,766.160)	(1,614.447)	(2,138.782)	(1,903.990)
Treat	1,828.374	2,637.437	-2,299.119	2,318.805	272.818	-1,962.937	-1,026.309
	(3,438.762)	(2,794.511)	(3,490.062)	(3,203.251)	(1,379.221)	(1,797.763)	(1,639.548)
Post	-861.113	1,827.464	-1,687.140	350.072	-4,438.087***	219.061	-369.351
	(2,929.413)	(2,111.727)	(2,973.699)	(2,593.112)	(1,149.430)	(1,526.345)	(1,416.326)
Constant	16,318.310	882.080	20,387.210	23,435.990	-118,231.900***	-71,320.040	1,322.501
	(13,713.650)	(10,693.640)	(13,627.920)	(15,307.260)	(29,367.750)	(127,896.000)	(45,540.830)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,000	20,000	20,000	20,000	119,940	83,446	66,608
Adj.R^2	0.314	0.373	0.289	0.332	0.292	0.314	0.346

Table 10. Robustness Checks

This table reports two robustness checks using data from Wave I. Panel A is the DID analysis when the treatment group is split into two, *Early* and *Late*, based on their arrival time in coupon acquisition. $TreatH$ and $TreatL$ are dummy variables that indicate whether an individual is in the early half or late half of the treatment group. Panel B reports the results for DID analysis on the restricted sample which drops observations with less than RMB 100 spending per month during the past six months. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Different Speed to Get Coupon		
	(1)	(2)
	Payamt	log(1+Payamt)
TreatE x Post	12,354.210***	0.790***
	(895.164)	(0.014)
TreatL x Post	13,406.640***	0.820***
	(899.313)	(0.014)
TreatH	241.734	0.484***
	(786.075)	(0.012)
TreatL	712.491	0.459***
	(794.028)	(0.012)
Post	-1,552.671**	0.070***
	(614.775)	(0.011)
Constant	28,867.140***	0.738***
	(2,618.740)	(0.048)
Controls	Yes	Yes
Obs.	600,000	600,000
Adj.R^2	0.318	0.483
Panel B: Restricted Sample		
	(1)	(2)
	Payamt	log(1+Payamt)
Treat x Post	12,567.310***	0.682***
	(959.884)	(0.014)
Treat	-752.351	0.332***
	(830.874)	(0.012)
Post	-1,363.686*	0.051***
	(696.542)	(0.011)
Constant	28,828.420***	-3.050***
	(3,309.497)	(0.079)
Controls	Yes	Yes
Obs.	369,528	369,528
Adj.R^2	0.314	0.345

Table 11. External Validity - Results from Guangxi

This table shows the DID results of the coupon program rolled out on April 23 in Guangxi. The dependent variables include total spending ($Payamt$), the log transformation of the total spending $log(1 + Payamt)$, the offline spending ($Offpayamt$) and the online spending ($Onpayamt$) in a period at individual level. The analysis is performed on PSM sample. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Payamt	log(1+Payamt)	Offpayamt	Onpayamt
Treat x Post	19,741.750***	2.180***	19,227.940***	366.535***
	(566.753)	(0.021)	(451.081)	(158.252)
Treat	1,531.699***	0.533***	2,263.968***	-42.690
	(531.260)	(0.020)	(432.148)	(173.839)
Post	-18,810.220***	-0.860***	-17,893.430***	-415.880***
	(406.744)	(0.016)	(322.169)	(112.813)
Age	1,489.529***	0.017***	1,870.943***	-346.672***
	(109.994)	(0.005)	(86.623)	(40.437)
Age2	-18.237***	-0.0003***	-20.718***	1.788***
	(1.430)	(0.0001)	(1.126)	(0.527)
Gender	-977.127**	-0.029***	3,633.631***	-4,564.657***
	(430.942)	(0.016)	(343.960)	(150.595)
Payamt_6m	0.134***		0.076***	0.033***
	(0.002)		(0.001)	(0.001)
log(1+Payamt_6m)		0.471***		
		(0.003)		
City fixed effect	Yes	Yes	Yes	Yes
Obs.	302,606	302,606	302,606	302,606
Adj.R^2	0.324	0.510	0.218	0.181
MPC	5.2	–	5.1	0.1
Elasticity	–	10.9	–	–

Table 12. Variable Definition

Variable	Definition
Payamt	Total consumption during a certain period (in cent).
log(1+Payamt)	The natural logarithm of one plus total spending.
OnPayamt	Online spending during a certain period (in cent).
OffPayamt	Offline spending during a certain period (in cent).
Treat	A dummy that equals one for treatment consumers and zero for control consumers.
Post	A dummy that equals one if an observation is from the coupon redemption period.
Post2	A dummy that equals one if an observation is from the week after the coupon redemption period.
Age	The age of consumers.
Age2	The square of consumers' age.
Gender	A dummy that equals one for male and zero for female.
Payamt_3up	The total spending during March 1-March19 (in cent).
Payamt_6m	The average monthly spending over the past six months (in cent).
log(1+Payamt_3up)	The natural logarithm of one plus *Payamt_3up*.
log(1+Payamt_6m)	The natural logarithm of one plus *Payamt_6m*.

Appendices

Table A1. Summary of Hangzhou Coupon

This table summarizes the information of six waves of coupon in Hangzhou from March 27 to the end of April.

Wave	Date	Coupon Details	Redemption Window	Government Subsidies(%)	Quantity
I	3/27	5 × "40-10" coupons	7 days	25%	2 million
I	4/1	5 × "40-10" coupons	7 days	25%	2.3 million
II	4/3	"100-20", "200-35", "300-45"	7 days	16.67%	1.5 million
III	4/10	5 × "40-10" coupons	7 days	25%	1.5 million
IV	4/20	5 × "40-10" coupons	7 days	25%	1.5 million
V	4/30	3 × "40-10" coupons	7 days	25%	3 million

Notes. Consumers who have acquired 3/27 coupon are not eligible for the 4/1 coupon.

Table A2. Heterogeneous Effect Analysis—Wave II

This table reports two robustness checks using data from Wave I (sample 1). Panel A is the DID analysis when the treatment group is split into two, *Early* and *Late*, based on their arrival time in coupon acquisition. $TreatH$ and $TreatL$ are dummy variables that indicate whether an individual is in the early half or late half of the treatment group. Panel B reports the results for DID analysis on the restricted sample which drops observations with less than RMB 100 spending per month during the past six months. The unit of regression coefficient is cent (RMB 0.01). Standard errors (in parentheses) are clustered at the individual level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Monthly Spending Terciles			Online Ratio Terciles		
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Mid	High	Low	Mid	High
Treat x Post	40,491.040***	34,385.780***	37,010.680***	42,678.270***	36,895.480***	31,854.000***
	(885.295)	(1,360.703)	(2,523.647)	(1,996.938)	(1,759.972)	(1,516.624)
Treat	5,441.806***	5,569.519***	5,340.317**	7,508.756***	2,462.106*	6,877.903***
	(651.420)	(1,023.504)	(2,177.380)	(1,732.051)	(1,410.924)	(1,218.707)
Post	-2,510.810***	-267.646	160.988	2,037.128	-1,524.789	-3,257.004***
	(577.062)	(971.334)	(1,803.110)	(1,401.515)	(1,261.576)	(1,056.877)
Constant	-2,790.023	9,044.438*	38,963.850***	-14,192.920	19,208.290***	3,358.621
	(2,743.218)	(4,698.915)	(13,696.930)	(9,119.859)	(7,031.446)	(4,874.882)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	103,650	102,308	99,906	98,780	95,020	102,236
Adj.R^2	0.094	0.042	0.267	0.346	0.275	0.236

	Huabei		Credit Usage		Age Group		
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Yes	No	Use	No use	≤ 30	31-40	≥ 41
Treat x Post	41,844.930***	46,604.750***	28,810.070***	41,625.060***	29,711.130***	38,979.100***	45,566.130***
	(3,824.156)	(3,092.123)	(3,851.442)	(3,754.709)	(1,576.882)	(1,948.190)	(1,614.303)
Treat	3,467.473	1,294.630	8,758.761***	4,509.575	5,122.745***	7,312.922***	5,349.721***
	(3,262.550)	(2,709.208)	(3,212.314)	(3,016.395)	(1,317.020)	(1,619.877)	(1,339.537)
Post	-4,546.129	-2,590.188	4,375.273*	496.046	-423.513	-2,317.573*	-134.069
	(2,766.703)	(2,141.489)	(2,637.213)	(2,557.637)	(1,109.380)	(1,367.249)	(1,136.270)
Constant	16,105.140	10,383.460	20,260.050	4,738.123	-81,559.760***	-60,592.390	-16,380.400
	(3,824.156)	(3,092.123)	(3,851.442)	(3,754.709)	(27,768.860)	(113,498.400)	(35,609.360)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,000	20,000	20,000	20,000	120,060	93,418	92,386
Adj.R^2	0.293	0.437	0.296	0.340	0.264	0.312	0.347

Figure 1. Baidu Search Index of "Consumption Coupon"

This figure shows the Baidu search index of the word "Consumption Coupon" over time. The peaks concide with the rollout of Hangzhou digital coupons.
Source: Baidu index.

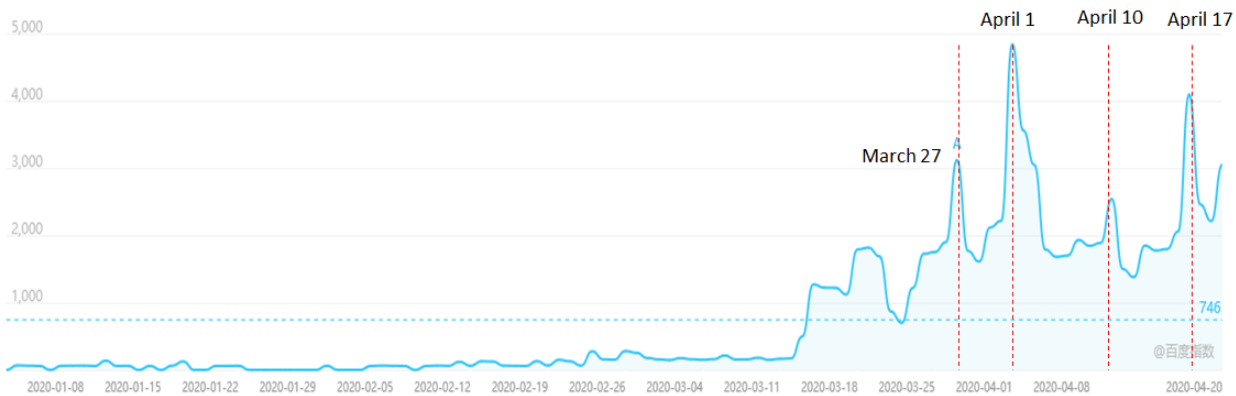
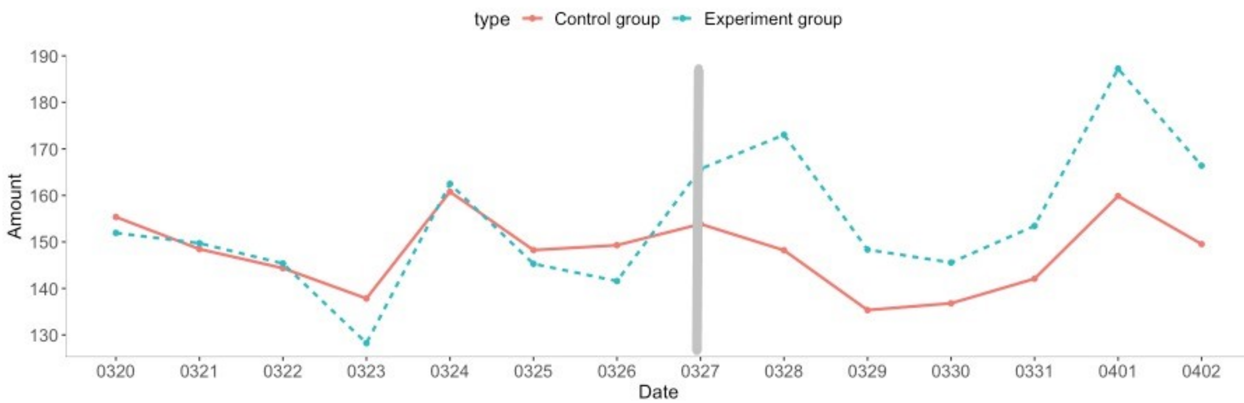


Figure 2. Screenshots of the Coupon Acquisition Page and Redemption Receipt

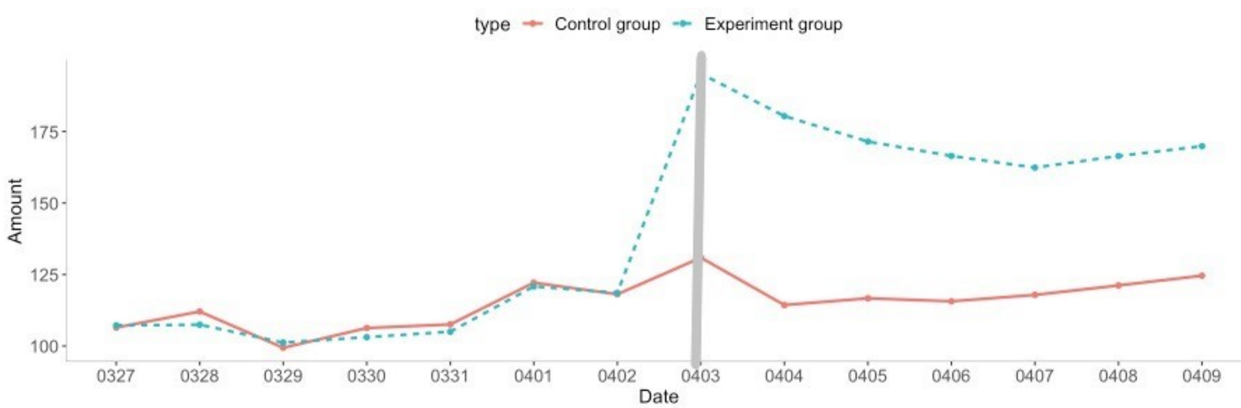
The upper figure shows the screenshot of the coupon acquisition page in Wave I . The lower part illustrates the coupon redemption. If an individual has a valid voucher in his Alipay account, then an offline transaction with the amount over the minimum purchase requirement would automatically redeem a voucher. The lower right figure shows a digital receipt of such transaction. The original total amount is RMB 77.9 and a coupon subsidy valued at RMB 10 is automatically applied to the transaction.

Figure 3. Time-trend of Spending

The figures show the time series of daily spending of the treatment group (in dotted green line) and the control group (in solid red line) with matching. The y-axis refers to the spending amount (in RMB yuan) and x-axis is date. The upper figure shows the data pattern of Wave I coupon rolled out on March 27. The low figure shows the data pattern (experiment/control group design 2) of Wave II coupon rolled out on April 3.



(A) Wave I coupon



(B) Wave II coupon

Figure 4. Distribution of Purchase Size – Wave I

These figures compare the distribution of purchase size (between 0 and RMB400) by the treatment and control groups in Wave I. The y-axis denotes density; the x-axis is purchase size (in RMB yuan). The upper figure shows the histogram of purchase size of the experiment group. The middle figure shows the histogram of the control group. The bottom figure shows the kernel density of the two, where the green shaded distribution refers to the experiment group and the orange shaded distribution refers to the control group.

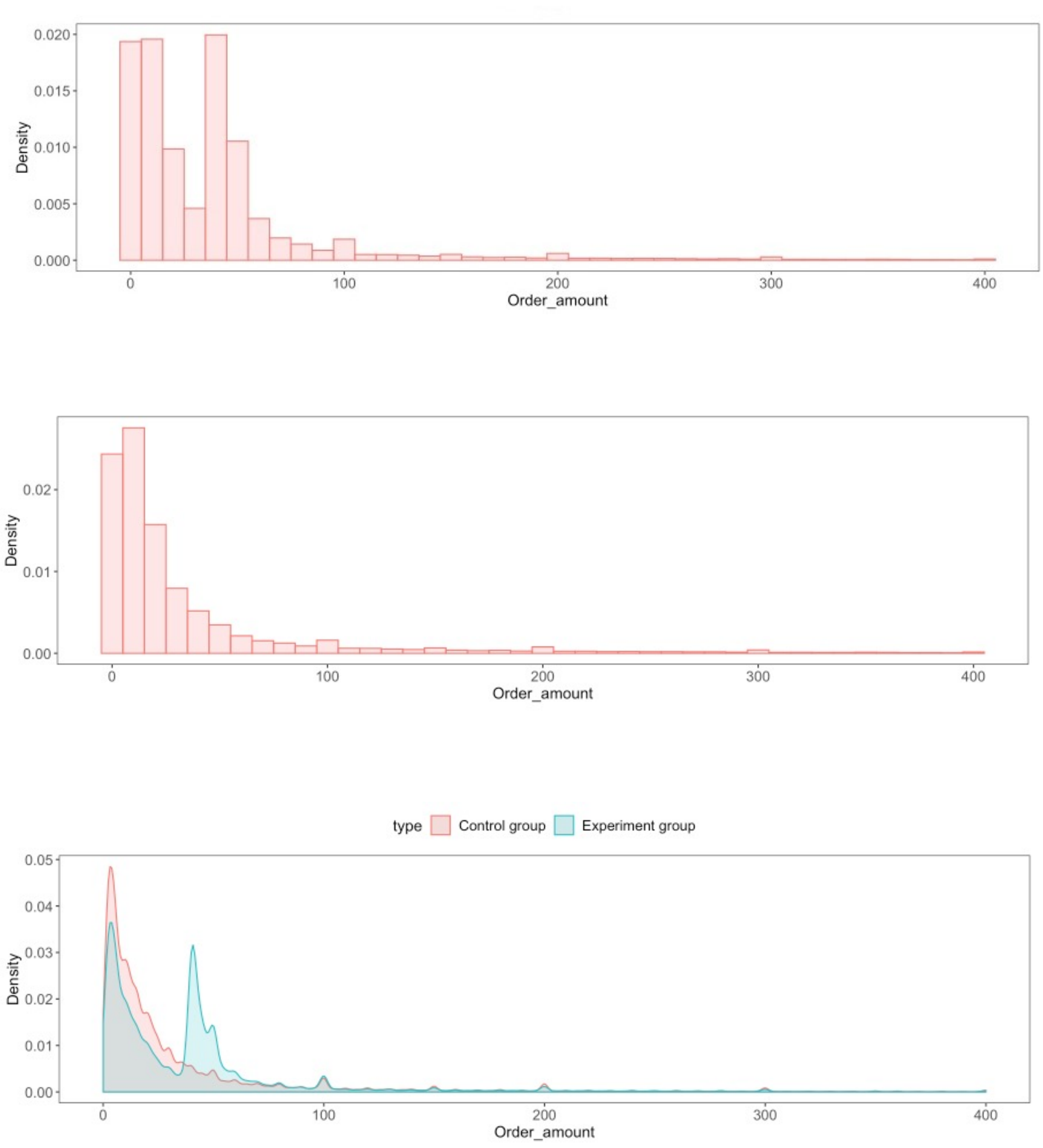


Figure 5. Distribution of Purchase Size – Wave II

These figures compare the distribution of purchase size (between 0 and RMB400) by the treatment and control groups in Wave II. The y-axis denotes density; the x-axis is purchase size (in RMB yuan). The upper figure shows the histogram of purchase size of the experiment group. The middle figure shows the histogram of the control group. The bottom figure shows the kernel density of the two, where the green shaded distribution refers to the experiment group and the orange shaded distribution refers to the control group.